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Emotion and Facial Recognition in Artificial Intelligence: Sustainable Multidisciplinary Perspectives and Applications

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Preface

The edited volume *Emotion and Facial Recognition in Artificial Intelligence: Sustainable Multidisciplinary Perspectives and Applications* presents an extensive exploration of the convergence between artificial intelligence (AI), psychology, neuroscience, human–computer interaction, and sustainable technological innovation. As AI systems evolve from analytical computation to empathetic and perceptive engagement, the ability to understand, interpret, and simulate human emotions has become a frontier in modern science and innovation. This book seeks to capture this transformative journey, providing a comprehensive and balanced perspective that encompasses the theoretical, empirical, technical, ethical, and policy-oriented dimensions of Emotion and Facial Recognition in AI.

Emotion recognition and facial analysis are now central to AI-driven human interaction, influencing applications ranging from education, healthcare, and business intelligence to law enforcement, mental health diagnostics, and governance. The ability of machines to perceive and respond to subtle human cues such as facial expressions, tone of voice, and microexpressions reflects an important step toward achieving human-like intelligence and contextual understanding. However, with this technological capability comes a spectrum of challenges, including bias in datasets, privacy concerns, ethical dilemmas, psychological impacts, and sustainability of AI systems. The book addresses these complexities through a multidisciplinary framework, integrating insights from data science, psychology, deep learning, legal studies, and educational technologies.

Chapters are summarized as follows:

The first two chapters introduce the conceptual and psychological underpinnings of emotion and its representation in computational systems. Chapter “[Introduction to Emotion Expression and AI](#)” provides the foundation for understanding how emotional data is represented, processed, and synthesized by intelligent systems. Chapter “[Theories of Emotions in Psychology](#)” delves into classical and modern emotion theories such as James–Lange, Cannon–Bard, Schachter–Singer, and appraisal models establishing the scientific framework that supports emotion modeling in AI.

Moving into the technological core, Chapters “[Classical Face Recognition: Geometric Models, Subspace Techniques and Local](#)

[Descriptors](#)”–“[Detection of Microexpressions and Subtle Emotions](#)” discuss algorithmic frameworks, feature extraction, and deep learning methods for emotion recognition. Chapter “[Classical Face Recognition: Geometric Models, Subspace Techniques and Local Descriptors](#)” presents classical facial recognition techniques including geometric and subspace models, forming the historical basis for modern recognition systems. Chapter “[Integrating Acoustic Feature Extraction and LSTM Models for Emotion Classification in Speech](#)” introduces acoustic emotion classification using LSTM networks, highlighting the fusion of audio and emotional analytics. Chapter “[Emotion Detection in Human-Machine Interaction Using ML Techniques](#)” bridges machine learning with affective computing, showing how machines perceive emotional patterns during real-time human-machine interaction. Chapter “[Real Time: 3D Facial Expression Recognition Using Improved AlexNet Convolutional Network via Deep-Emotion](#)” introduces advanced 3D modeling using an improved AlexNet architecture for deep emotion analysis, while Chapter “[Feature Aggregation for Efficient Continual Learning of Complex Facial Expressions](#)” emphasizes continual learning frameworks for sustained emotion recognition. Chapter “[Advanced Techniques in Facial Landmark Detection and Feature Extraction for Emotion-Aware AI Systems](#)” provides an in-depth analysis of facial landmark detection and feature engineering, and Chapter “[Detection of Microexpressions and Subtle Emotions](#)” explores the intricate science behind microexpression and subtle emotion detection, which is crucial for forensic and behavioral applications.

The next set of chapters, Chapters “[Navigating the Future of Emotion AI: Technical Barriers, Ethical Concerns, and Sustainable Advancements](#)”–“[Integrating Positive Emotions to Support Self-Directed Learning](#)”, navigate interdisciplinary domains connecting Emotion AI to sustainability, ethics, mental health, and education. Chapter “[Navigating the Future of Emotion AI: Technical Barriers, Ethical Concerns, and Sustainable Advancements](#)” provides a critical discussion on the technical barriers, ethical challenges, and sustainability frameworks in Emotion AI development. Chapter “[Emotion AI in Mental Health](#)” connects affective computing with mental health diagnostics, illustrating its potential in early emotion-based disorder detection and therapy. Chapter “[A Conceptual Framework for Adaptive Student Assessment Using AI-Driven Recommendations and Facial Expression Recognition](#)” and

Chapter “[Integrating AI-Driven Facial Emotion Recognition into E-Learning Systems: Sustainable Educational Markets Through Interdisciplinary Innovations](#)” expand the educational dimension, introducing frameworks for adaptive learning and AI-driven student assessment through emotion recognition in e-learning platforms. Chapter “[Integrating Positive Emotions to Support Self-Directed Learning](#)” continues this theme by exploring positive psychology and emotion integration to support self-directed learning and educational resilience.

The final segment, Chapters “[Emotion AI in Business and Customer Services](#)”—“[Emotion AI: Challenges and Future Directions](#)” broaden the discussion to industrial, legal, and futuristic perspectives. Chapter “[Emotion AI in Business and Customer Services](#)” showcases the use of Emotion AI in business intelligence, marketing, and customer interaction systems, highlighting data-driven personalization and emotion analytics in service industries. Chapter “[Deep Learning Approaches and Technical Challenges in Facial Emotion Recognition \(FER\)](#)” consolidates deep learning methodologies for facial emotion recognition (FER) and presents critical challenges associated with data imbalance, real-time performance, and interpretability. Chapter “[Emotion Recognition and the Law: Bridging Technology and Human Rights](#)” introduces a powerful discussion on emotion recognition and the law, exploring the interface between human rights, privacy, and AI regulation. Finally, Chapter “[Emotion AI: Challenges and Future Directions](#)” concludes the book by synthesizing emerging research trends, future applications, and ethical imperatives for sustainable emotion AI development.

This book is the result of collaborative scholarship from a diverse community of researchers, technologists, psychologists, and policymakers from around the world. Each contributor brings unique expertise, ensuring that the reader gains a holistic understanding of how emotional intelligence and AI can coexist in a manner that enhances human machine collaboration without compromising ethical and societal values.

In an era where machines are learning not only to think but also to “feel”, the objective of this volume is to inspire further inquiry into emotionally aware, ethically aligned, and sustainable AI ecosystems. It serves as a valuable reference for academicians, practitioners, students, policymakers, and innovators seeking to understand how emotion and

intelligence can be harmonized to shape the next generation of human-centric AI technologies.

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About the Editors

Dr. Khadija Slimani a member of IEEE, has built a notable career in both academia and research. She earned her Ph.D. through a collaborative program between the University of Ibn Tofail in Morocco and the University of Technology of Belfort Montbéliard (UTBM) in France. This joint supervision highlights her commitment to academic excellence and her skill in integrating cross-cultural research environments. Dr. Slimani's doctoral research covered a broad range of topics, including machine learning, deep learning, pattern recognition, and computer vision, with a specific focus on academic emotion recognition.

Her interdisciplinary approach, enriched by experiences in both Moroccan and French academic settings, has contributed significantly to the global perspective of her work. After completing her Ph.D., Dr. Slimani advanced her expertise through a postdoctoral position at the University of Poitiers, France, where she concentrated on Objects DRI (Detection, Recognition, and Identification). Her innovative use of AI methodologies aimed to enhance video content filtering for improved security, demonstrating her ability to address complex problems on an international scale. In addition to her research, Dr. Slimani has made substantial contributions to the field of telecommunications. Her interests extend to Next-Generation Networks (NGN), 5G, and 6G technologies, where she investigates their implications and potential advancements. This focus on cutting-edge telecommunications technology underscores her role in shaping the future of network infrastructure and communication systems. Dr. Slimani has also been actively involved in teaching at several prestigious engineering schools in Paris, covering modules such as data science, deep learning, machine learning, databases, computer vision, and telecommunications. She currently holds the position of Associate Professor at the Graduate School of Automatic Electronic Computing in Paris. Her scholarly achievements include over 21 published articles in esteemed journals and conferences, with an impressive h-index of 10 in Scopus. Dr. Slimani has also served as



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2025 (Takshashila Institution—Indian Police Foundation) also serving as scientific and technical committee member in international conferences at world class level. Beyond his research and teaching, he contributes as a reviewer for reputed journals such as MDPI, Springer, Elsevier, IntechOpen, River Publishers, and IJBPS. He is also an active member of professional bodies including the Internet Society (ISOC) Delhi and Mumbai Chapters, ACM, and IEEE.

Dr. Samira Khoulji is a professor in electronics, telecommunications, and computer science at the National School of Applied Sciences in Tetuan (ENSATE) of Morocco, where she also serves as the coordinator for the Telecommunications and Networks Engineering program for engineering students. She holds the position of director of the “Innovative Systems Engineering” (ISI) research laboratory. Previously, she was the head of the Department of Statistics and Computer Science at the multidisciplinary faculty in Tétouan, where she was responsible for the professional programs in “Tourism and ICT” and “Management of Information Systems (MSI)” as well as the coordinator for the Specialized Master’s program in “Management of Information Systems and Multimedia (MSIM). Dr. Samira Khoulji has actively participated in various committees and councils and has coordinated teaching modules in physics, computer science, and telecommunications at the multidisciplinary faculty and ENSAT in Tétouan. As a researcher, she is the author or co-author of numerous research articles and has contributed as a member to multiple national and international conference and meeting committees. She has also been involved in several European research projects, particularly in the fields of professional integration, tourism, and renewable energy. Dr. Samira Khoulji has organized several national and international events and conducted numerous training workshops for doctoral candidates. Her commitment to research spans many years, with her work primarily



focusing on areas such as intelligent systems, machine learning, big data, sensor systems, deep learning, mobile communications, Internet of Things, cybersecurity, and computer vision, including facial detection, matching, and recognition. Please provide high-resolution photo for Dr. Samira Khouljiwe dont have any another photo. you can adjust according to your level.

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Introduction to Emotion Expression and AI

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Abstract

This chapter discusses the interaction between human emotional experiences and machine learning frameworks, relating computational methods of emotion generation and recognition to psychological concepts like Ekman's basic emotions and dimensional theories. We discuss how such models as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers perceive the facial, vocal, and textual features to identify emotions, and also synthesize artificial expressions. Notably, the ethical considerations of privacy, algorithmic bias, manipulation, and accountability are the key concerns that the chapter considers as the core of responsible AI development. The examples of emotion AI in practice (e.g., mental health screening, customer service chatbots, retail personalization) demonstrate how it can transform the

world, whereas the questions about the emotional understanding and the effects on society are open-ended, which preconditions the future research. Overall, the chapter suggests that the success of emotion AI lies in the ability to balance the innovativeness with the ethical rigor, so that the technology should improve, but not corrupt, human connection.

Keywords Emotion expression – AI – CNN – Facial emotion recognition

1 Foundations of Emotion Expression

1.1 Defining Emotions: Psychological Perspectives

Emotions are subjective, momentary, triggered by internal or external events, characterized by three interrelated factors: physiological (e.g., a racing heart), outward (e.g., smiling) and conscious (e.g., happiness) aspects. There are two basic frameworks of emotions that psychologists usually divide them into:

- **Categorical Models:** Propose discrete “basic emotions” (e.g., joy, anger, fear) supported by Paul Ekman’s cross-cultural research, which identifies universal facial expressions across diverse societies.
- **Dimensional Models:** Frame emotions as points on a continuum of valence (positive/negative), arousal (calm/excited), and dominance (controlled/powerful), as described in James Russell’s circumplex model.

Both perspectives are valuable: categorical models simplify recognition (e.g., labeling a smile as “happy”), while dimensional models capture nuance (e.g., distinguishing “excited joy” from “content joy”) [28]. We adopt a hybrid approach because real-world emotions rarely fit neatly into boxes—they exist on spectra, shaped by context.

1.2 Human Emotion Expression: Channels and Universality

Humans express emotions through four primary channels, each with universal and culturally variable elements. **Facial expressions** (e.g., raised eyebrows for surprise, furrowed brows for anger) are the most studied: Ekman’s work shows six basic expressions are recognizable across 50+ cultures, though intensity and context modify them (e.g., a “polite smile” in Japan vs. a “genuine smile” in the U.S.) [3, 34]. **Vocal prosody**—the tone, pitch, and rhythm of speech—conveys emotion even without words (e.g., a

trembling voice for fear). **Bodily movements** (e.g., crossed arms for defensiveness, open posture for openness) and **verbal content** (e.g., “I’m fine” said sarcastically) complete the picture. Universality arises from shared biology (e.g., amygdala activation for fear), but culture shapes *display rules* (e.g., suppressing anger in formal settings) [13, 21]. Because AI systems have to recognize simple emotional signals as well as accommodate a range of possible cultural situations, this is an important balance between universality and diversity.

1.3 Computational Models of Emotion: From Theory to Algorithms

In order to create AI that communicates with human emotions, we put psychological theories into computational models. Categorical models are the ones that motivate classification algorithms (e.g., convolutional neural networks [CNNs] that identify facial expressions as either anger or joy). Dimensional models are used to power regression or clustering (e.g. predicting valence/arousal scores with text using transformer models). Hybrid models combine categorical and dimensional models, including the classification of an expression as being happy (categorical) and the measurement of its high arousal (dimensional) [Z, 41, 42]. We choose such models to trade off between simplicity (which is crucial when dealing with real-time applications such as customer service bots) and granularity (which is imperative when a research is conducted such as mental health screening). One of the most difficult tasks is to bridge the so-called empathy gap: AI should not be able to read emotions but understand their contextual interpretation (e.g., a face is sad, but it might mean grief or exhaustion). This will require the combination of various channels, such as facial, vocal, and textual, to reduce ambiguity, which is the way humans perceive emotional stimuli.

2 AI Systems for Emotion Recognition

Here we discuss the way AI identifies human emotions through sensory data of four main modalities, which include facial, vocal, physiological, and textual, and the machine learning algorithms that make this possible. We also address key challenges that limit current systems’ accuracy and fairness.

2.1 Sensory Input Modalities

We design AI systems to extract emotional cues from human behavior using four distinct channels, each with unique advantages and constraints:

- **Facial Expressions:** Computer vision algorithms analyze video or static images to identify micro-expressions (e.g., lip tightening for anger, cheek raising for joy) and macro-expressions (full smiles, frowns). Convolutional neural networks (CNNs) excel here, as they automatically learn spatial patterns in pixel data. However, facial recognition [[23](#), [30](#)] struggles with poor lighting, occlusions (e.g., masks), or extreme angles—common in real-world scenarios.
- **Vocal Prosody:** Audio signals provide rich emotional data through tone, pitch, rhythm, and pauses. For example, a trembling voice indicates fear, while a rapid, high-pitched tone suggests excitement. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks process sequential audio features, capturing temporal dynamics. Yet background noise (e.g., crowds, traffic) often corrupts vocal cues, reducing reliability [[44](#)].
- **Physiological Signals:** Wearable sensors (e.g., smartwatches, EEG headsets) measure biometric changes linked to emotion, such as increased heart rate (arousal), skin conductance (stress), or brainwave activity (engagement). While these signals are objective and hard to fake, they require invasive hardware and struggle with individual variability (e.g., a athlete’s baseline heart rate differs from a sedentary person’s) [[41–43](#)].
- **Textual Content:** Natural language processing (NLP) analyzes written or spoken language to infer sentiment (e.g., “I’m thrilled” = positive) and intent (e.g., “Can you help?” = neutral/help-seeking). Transformer models (e.g., BERT, GPT) dominate here, as they handle context and long-range dependencies [[24](#), [30](#)]. However, text alone misses nonverbal cues—sarcasm (“Great, another meeting”) or irony (“Nice weather—pouring rain!”) often confuse AI.

We can combine these modalities (multimodal fusion) to improve robustness. For instance, a system might use facial data to confirm a “smile” detected in text, reducing false positives (Fig. [1](#)).



Fig. 1 Facial expressions corresponding to basic emotions (Ekman’s 6 + 2 extended)

2.2 Machine Learning Approaches

To convert raw sensory data into emotional labels, we leverage three core machine learning paradigms, each tailored to the structure of the input:

- **Convolutional Neural Networks (CNNs):** Ideal for spatial data (facial images, spectrograms of speech). CNNs apply filters to detect edges, textures, and shapes—critical for recognizing a furrowed brow or a rising pitch. For example, a CNN trained on the FER2013 dataset (48,000 facial images) achieves ~70% accuracy in classifying basic emotions.
- **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTMs):** Suited for sequential data (vocal audio, text). RNNs process inputs step-by-step, retaining memory of previous steps—essential for capturing the progression of a sentence (“I was happy... until I saw the bill”) or a speaker’s tone shift. LSTMs improve upon RNNs by addressing the “vanishing gradient” problem, allowing them to remember longer contexts.
- **Transformer Models:** Revolutionized NLP and multimodal tasks. Transformers use self-attention mechanisms to weigh the importance of each word (or pixel) in relation to others, enabling them to understand nuanced language (e.g., “I’m fine” said with a sigh) or fuse facial and textual data. For instance, a transformer might combine a frowning face with the text “This is amazing” to flag sarcasm [4, 9, 22].

We choose these models because they balance accuracy and efficiency. CNNs handle visual data quickly, LSTMs manage temporal sequences, and transformers excel at context—key for real-time applications like customer service bots or mental health screening tools (Table 1).

Table 1 Comparison of deep learning models for emotion recognition and analysis

Model type	Core mechanism	Typical use cases	Key advantages	Key limitations	Real-world impact examples
CNNs (convolutional neural networks)	Extracts spatial features (e.g., edges, textures) through convolutional And pooling layers	Facial expression classification (e.g., Ekman's six emotions); audio spectrogram analysis	Automatic feature learning Highly efficient for image and audio data	Sensitive to lighting variations and occlusion Limited handling of temporal dependencies	Snapchat filters (real-time facial effects); Amazon Alexa (voice wake-word detection)
RNNs/LSTMs	Processes sequential data (text, audio) using hidden states; LSTMs overcome vanishing gradient issues	Speech emotion recognition (e.g., customer service calls); text sequence prediction (e.g., empathetic chat responses)	Captures temporal dependencies Lower computational cost than transformers	Slow inference due to sequential nature Prone to overfitting on small datasets	Google Assistant (speech recognition); Twitter sentiment analysis
Transformers	Employs self-attention to determine input importance; enables parallel processing for efficiency	Multimodal fusion (facial + text for chatbots); generative tasks (e.g., emotion-aware emails)	Captures long-range dependencies State-of-the-art performance for NLP and multimodal tasks	Requires large datasets Computationally expensive Risk of “hallucination”	ChatGPT (text generation); Microsoft Teams (caption translation)
GANs (generative adversarial networks)	Adversarial setup: generator produces synthetic data; discriminator	Synthetic emotion generation (e.g., deepfakes, virtual influencers); virtual avatar expressions	Generates realistic and high-quality outputs Flexible with unstructured	Training instability (mode collapse) Ethical and misuse concerns (deepfakes)	DeepFaceLab (deepfake creation); Unreal Engine (virtual character animations)

Model type	Core mechanism	Typical use cases	Key advantages	Key limitations	Real-world impact examples
	evaluates its realism		data (images, audio)		
GNNs (graph neural networks)	Utilizes message passing between nodes to model relationships in graph-structured data	Social emotion analysis (e.g., viral sentiment in online communities); emotion-driven recommendation systems (e.g., TikTok feeds)	Captures relational and collective emotion dynamics Effective for sparse or structured data	High computational cost for large graphs Performance depends on graph structure quality	Twitter trend analysis; TikTok recommendation systems

2.3 Challenges in Emotion Recognition

Despite progress, AI systems face significant hurdles in reliably detecting human emotions:

- **Ambiguity:** The same physical cue can signal multiple emotions. A frown might indicate anger, concentration, or sadness—context is critical, but AI often lacks the world knowledge to disambiguate. For example, a “neutral” face in a job interview could be interpreted as bored or serious, depending on cultural norms [18, 27].
- **Context Dependency:** Emotions are situational. A laugh at a comedy show is joyful, but the same laugh at a funeral is inappropriate (and likely forced). Current systems rarely incorporate contextual metadata (e.g., location, event type), limiting their ability to adapt.
- **Algorithmic Bias:** Training data often reflects demographic imbalances. For instance, facial recognition models trained primarily on light-skinned faces perform poorly on darker skin tones, misclassifying emotions like “anger” or “disgust” at higher rates. In the same manner, the vocal prosody models can fail to identify emotions among non-native speakers of English because the accent variation can manipulate the prosodic characteristics.
- **Privacy Concerns:** There are significant ethical concerns with the gathering of biometric information, such as heart rate and facial scans. Individuals often have no idea that their emotional states are being monitored; for example, a fitness tracker may be measuring stress levels

if an individual is performing work activities without obtaining his or her explicit consent.

Such issues highlight the gap between artificial intelligence's technical precision and the complex, highly nuanced nature of human feeling. These need to be solved jointly by experts: ethicists need to establish clear guidelines for ethical and responsible use, engineers need to enhance model dependability, and psychologists need to enhance emotional models.

3 AI-Driven Emotional Generation

We then shift our focus to the complimentary process—the generation of emotional responses—based on our previous discussion of how artificial intelligence understands human emotions (Sect. 2). It is crucial in developing AI systems that can communicate naturally and in a human-like manner, ranging from empathetic chatbots to virtual assistants that respond appropriately to users' emotions. This chapter investigates the goals of synthetic emotion, describes the approaches to producing affective outputs across different media, and evaluates how effectively these systems convey contextual appropriateness and genuineness.

3.1 Synthetic Emotion in Machines: Goals and Applications

Synthetic emotion includes the AI-created cues that recreate or instigate the human emotional conditions. Its aims are dual:

1. Improve User Experience: Increase the level of interest and connection.
As an illustration, a customer care robot that replies to frustration with a cool and reassuring voice calms down the user.
2. Enabling Adaptive Behaviour: Give the AI the opportunity to adapt itself to the emotion of a user. Educational software, for instance, might simplify a math problem if it detects confusion (via facial or textual cues) [2, 38, 45].

Applications span industries:

- **Healthcare:** Virtual therapists that deliver supportive messages to patients with depression.

- **Gaming:** Non-player characters (NPCs) that react dynamically to player emotions (e.g., cheering for a win or consoling after a loss).
- **Retail:** Chatbots that use humor or urgency to nudge purchases (e.g., “Don’t miss out—this sale ends soon!”).

A key distinction exists between **simulated emotion** (mimicking outward signs, e.g., a smile) and **felt emotion** (true internal states, which AI cannot experience). Most systems focus on simulation, as felt emotion remains beyond current technological reach [20, 29, 39].

3.2 Techniques for Emotional Output: Text, Speech, and Visuals

Generating emotional outputs requires modality-specific techniques, often combined for richer interactions:

Text-Based Emotion Generation

Natural language processing (NLP) models are the backbone of text-based emotional generation. **Transformers** (e.g., GPT-4, BERT) are fine-tuned on datasets like *EmpatheticDialogues* (pairs of user statements with empathetic responses) to produce emotionally appropriate replies. For example:

- Input: “I failed my exam.”
- Output: “That sounds really tough—would you like to talk about what went wrong?” Techniques include:
- **Sentiment Transfer:** Adjusting the tone of a message (e.g., turning a neutral statement into an encouraging one).
- **Contextual Adaptation:** Using dialogue history to tailor responses (e.g., remembering a user’s stress about work and referencing it later).

Speech-Based Emotion Generation

Neural text-to-speech (TTS) systems with **prosody control** generate emotional vocal outputs. Models like *Tacotron 2* or *WaveNet* manipulate pitch, volume, and rhythm to convey emotions:

Anger: Sharp, high-pitched tones with rapid speech.

Sadness: Low, slow, monotone delivery.

Advanced systems integrate **emotion embeddings** (numerical representations of emotions) into TTS pipelines, allowing developers to specify desired emotions (e.g., “output a cheerful tone”) [6, 19, 36] (Fig. 2).

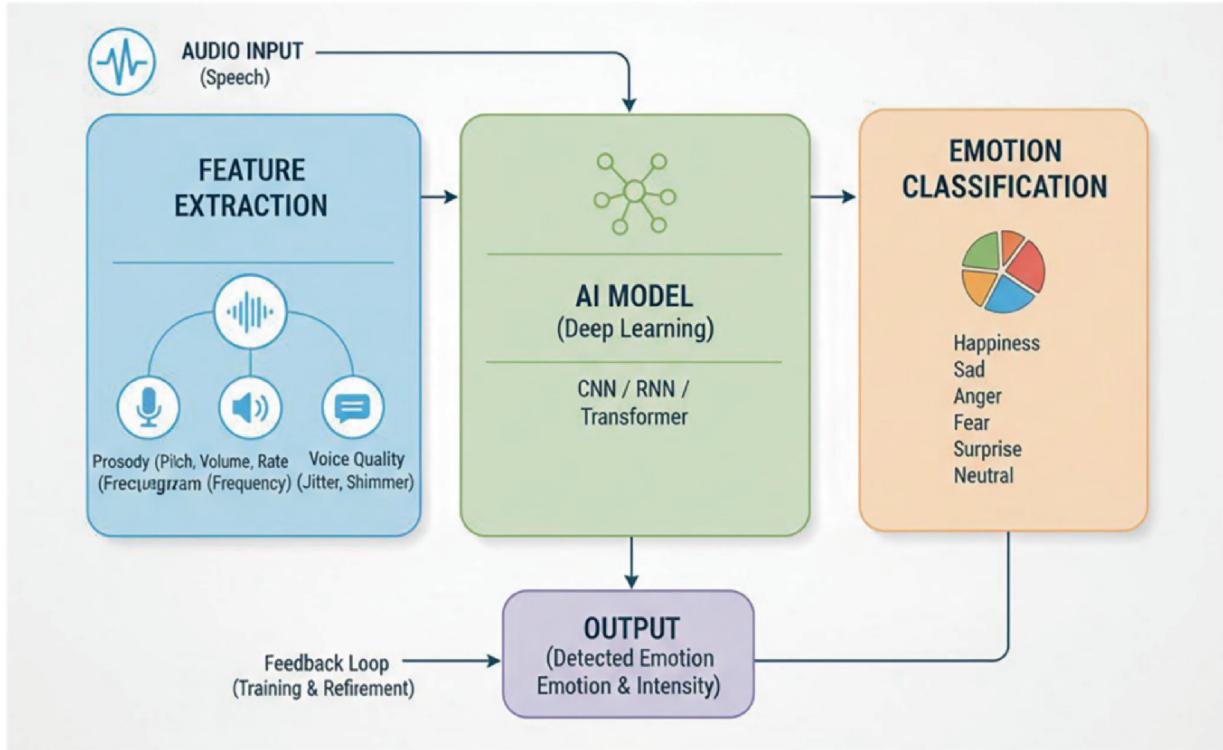


Fig. 2 AI voice emotion analysis workflow

Visual-Based Emotion Generation

Computer graphics and animation drive visual emotional outputs.

Generative Adversarial Networks (GANs) synthesize realistic facial expressions (e.g., a surprised face) by training on datasets like *Facial Action Coding System (FACS)*. Motion capture technology records human body language (e.g., slumping shoulders for sadness) and translates it to virtual avatars.

Multimodal fusion—combining text, speech, and visuals—creates more immersive experiences. For example, a virtual assistant might say “I’m sorry to hear that” (speech) while displaying a sympathetic facial expression (visual) and offering a solution (text) [12, 32, 33].

3.3 Evaluating Generated Emotion: Validity, Appropriateness, and User Perception

Evaluating synthetic emotion is challenging because “good” emotion depends on context and user expectations. We use a mix of **objective** and **subjective** metrics:

Objective Metrics

Consistency: Does the output match the intended emotion? For example, a “happy” text response should have positive sentiment scores (measured by NLP tools like VADER).

Diversity: Can the system generate a range of emotions (e.g., not just happiness but also anger or fear)?

Latency: Is the response timely? Delays can disrupt emotional flow (e.g., a bot taking 10 s to reply to a user’s frustration).

Subjective Metrics

- **Realism:** Do users perceive the emotion as genuine? Surveys ask participants to rate how “natural” a response feels (e.g., “On a scale of 1–5, how believable was the bot’s sympathy?”).
- **Appropriateness:** Does the emotion fit the context? A bot that laughs at a user’s complaint about a broken product is inappropriate—even if the laughter is realistic.
- **Engagement:** Do users prefer emotional AI over neutral systems? Studies track metrics like conversation length or repeat usage [[17](#), [26](#)].

Challenges in Emotional Generation

Despite advances, AI-generated emotion faces significant hurdles:

- **Authenticity Gap:** Simulated emotions often lack the subtlety of human expression (e.g., a bot’s “sadness” may not convey true empathy).
- **Context Blindness:** Systems struggle to adapt to dynamic situations (e.g., a bot that continues to cheer a user who is clearly upset).
- **Scalability:** Generating diverse emotions for global audiences requires training data that represents cultural differences (e.g., a “thumbs-up” gesture is positive in the U.S. but offensive in Greece).

Ethical Risks

- Excessively manipulative emotional outputs—for instance, a bot employing flattery to drive purchases—can exploit user vulnerability. To maintain trust, it is critical to make people aware of the emotional constraints of AI (Fig. 3).

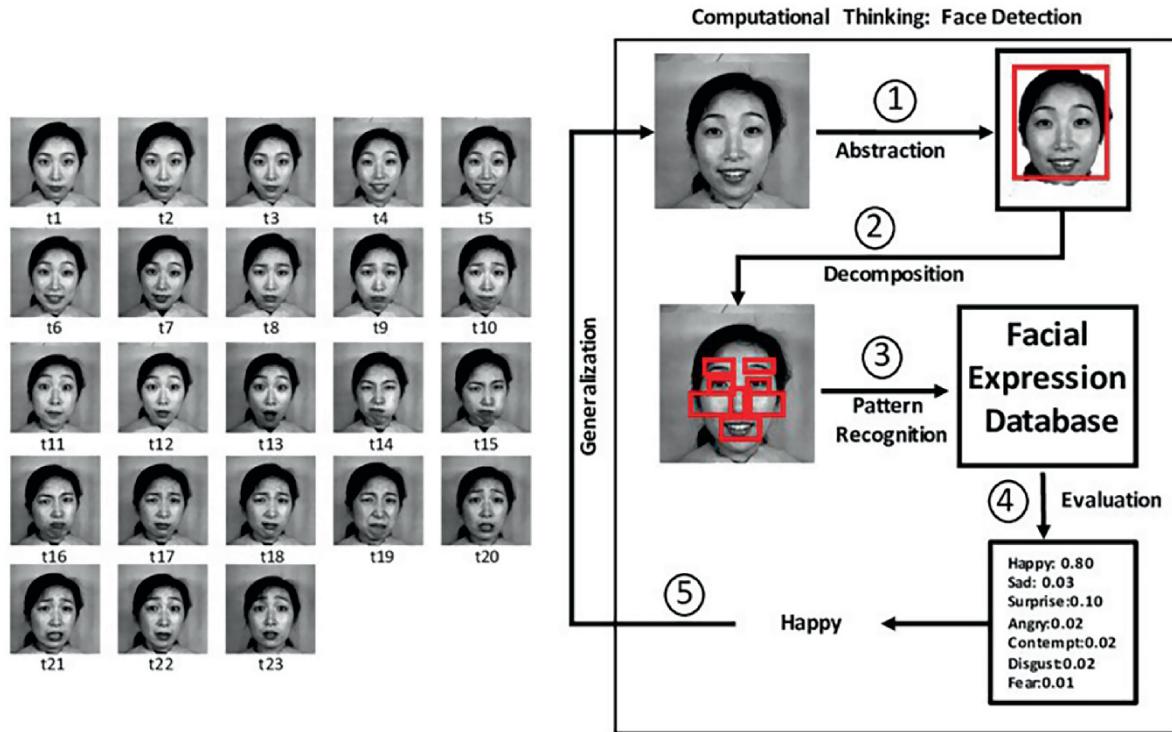


Fig. 3 Computational workflow for facial expression recognition

The challenge of translating human emotions into forms that machines can interpret is brought out in this part. Although AI can imitate emotional responses, there is still need to research on how there is a distinction between imitation and genuine understanding. The ethics of emotion AI are investigated in the subsequent section, which examines how and when these technologies impact social interaction, privacy concerns, and core human values.

4 Ethical and Societal Implications

There are some grave ethical and social concerns raised by the increasing ability of AI systems to recognize and generate human emotions. The sensitivity of emotional data, the possibility of misuse, and the influence on human autonomy are the reasons of these issues. Here, we discuss four

main issues including privacy, bias, manipulation, and accountability and the ways to harm mitigation.

4.1 Privacy Concerns in Emotion Data Collection

The use of AI systems is associated with deeply ethical and social concerns as they grow able to perceive and produce human emotions. The sensitivity of emotional data, the possibility of misuse, and the influence on human autonomy are the reasons of these issues. Here, we discuss four main issues including privacy, bias, manipulation, and accountability and the ways to harm mitigation. For example:

- The fact that a fitness tracker has recorded a high heart rate during a meeting might suggest that the person is experiencing anxiety at work.
- A home camera that is capable of analyzing facial expressions can record when a user is sad after phone conversation.

The threat of unauthorized access is urgent: compromised databases may reveal vulnerable groups (e.g., domestic abuse victims) or be sold off to third parties (e.g., refused to cover by insurance companies due to the presence of such emotions). Even with consent, users often lack awareness of how their data is used—studies show 60% of people do not read privacy policies detailing emotion data collection [[5](#), [16](#), [37](#)].

To protect privacy, we advocate for **explicit, granular consent** (e.g., “Allow this app to access your facial expressions for emotion recognition?”) and **data minimization** (collecting only necessary information). Regulations like the EU’s GDPR and California’s CCPA already restrict biometric data, but enforcement remains inconsistent globally.

4.2 Algorithmic Bias and Fairness in Emotion AI

Emotion AI inherits biases from training data, leading to discriminatory outcomes. For example:

- **Facial Recognition:** Models trained predominantly on light-skinned faces misclassify emotions (e.g., “anger”) in dark-skinned individuals at 34% higher rates.
- **Vocal Analysis:** Accents (e.g., Southern U.S. dialects) or speech impairments (e.g., stuttering) are often misinterpreted as “frustration” or “confusion,” penalizing non-standard speakers.

- **Text-Based Sentiment Analysis:** NLP models associate African American Vernacular English (AAVE) with negative sentiment, even when the content is neutral.

These biases perpetuate systemic inequities: a hiring bot that rejects candidates with “anxious” facial expressions may discriminate against neurodiverse applicants, while a loan approval system that flags “stress” in low-income users could deny financial aid [8, 14, 40].

Mitigation requires **diverse, representative datasets** (e.g., including faces of all skin tones, accents, and linguistic styles) and **bias auditing tools** (e.g., IBM’s AI Fairness 360) to detect and correct disparities. However, achieving full equity is challenging—cultural differences in emotional expression (e.g., a “neutral” face in Japan vs. a “serious” face in the U.S.) complicate universal standards.

4.3 Manipulation and Exploitation Risks

AI’s ability to generate emotional responses creates opportunities for manipulation. For example:

- **Persuasive Technology:** Ads that use “urgency” (e.g., “Only 2 left!”) or “social proof” (e.g., “90% of users loved this!”) trigger impulsive buying by exploiting fear of missing out (FOMO).
- **Deepfakes and Synthetic Media:** AI-generated videos or voices mimicking celebrities or politicians can spread misinformation (e.g., a fake clip of a CEO “admitting” fraud).
- **Emotional Labor Automation:** Customer service bots that feign empathy (e.g., “I’m so sorry you’re frustrated!”) may placate users but mask unresolved issues, eroding trust in institutions.

The line between helpful and harmful manipulation is thin. A therapy bot that uses gentle encouragement is beneficial, but one that pressures a user to disclose personal trauma crosses an ethical boundary [11].

Regulatory frameworks like the EU’s Digital Services Act (DSA) prohibit “dark patterns” (deceptive design) and require transparency in AI-generated content. However, global coordination is lacking, and bad actors often exploit legal loopholes [1, 25] (Table 2).

Table 2 Ethical and governance issues in emotion AI systems

Issue category	Specific concerns	Potential risks	Mitigation strategies
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Issue category	Specific concerns	Potential risks	Mitigation strategies
Privacy	Biometric surveillance in public spaces, data collection from wearables (e.g., smartwatches), and digital footprints on social media platforms	Identity theft, emotional profiling, and stalking	Implement anonymization and data minimization; obtain explicit user consent; adopt differential privacy and federated learning techniques
Bias and fairness	Demographic imbalance in training data, intersectional bias affecting marginalized communities, and lack of representation for low-resource languages	Discriminatory outcomes in hiring or lending, medical misdiagnosis, and exclusion in voice/emotion analysis systems	Use diverse and representative datasets; conduct fairness audits; apply contextual calibration; adopt participatory design approaches
Manipulation	Deepfakes and synthetic media, emotion-triggered advertising, and emotional labor automation in chatbots	Erosion of public trust, psychological harm, and exploitation of vulnerable groups (e.g., children, minors)	Strengthen content moderation; enforce transparency mandates; promote user awareness and empowerment; develop ethical design guidelines
Accountability	Black-box algorithmic decisions and lack of model explainability	Unfair or opaque decisions (e.g., in judicial or corporate contexts), accountability gaps, and public distrust	Incorporate explainable AI (XAI); ensure human-in-the-loop oversight; conduct independent audits and algorithmic impact assessments

4.4 Accountability and Human Oversight

When emotion AI makes flawed decisions (e.g., a security system flagging a “suspicious” person based on a misread facial expression), who is responsible? The developer? The company deploying the system? The user?

Current laws (e.g., product liability statutes) were not designed for AI, leaving gaps in accountability. For example:

- A hospital using an emotion-recognition tool to assess pain may face lawsuits if the tool fails to detect suffering in a non-verbal patient.
- A social media platform using sentiment analysis to censor “negative” posts could suppress legitimate criticism.

To address this, we recommend **explainable AI (XAI)**—systems that justify their emotional classifications (e.g., “We flagged this post as ‘angry’ because it contains aggressive language and capital letters”). Human

oversight is also critical: no AI should make high-stakes decisions (e.g., parole recommendations) without human review.

Ultimately, fostering accountability necessitates a multi-stakeholder framework: developers must explicitly record their systems' constraints, organizations should regularly assess for biases, and governing bodies need to implement regulatory measures. Without these protections, emotion AI will be able to undermine increasingly public trust [15, 35].

This discussion highlights how emotion AI is a sociotechnical complex system in nature and not merely a technical device. Ensuring a balance between innovation and responsibility is crucial to its moral use, ensuring that advances in AI support instead of degrading human dignity. Consequently, the subsequent section discusses potential future directions that these ethical principles will dictate as emotion AI continues to evolve.

5 Real-World Applications and Limitations

The following section will examine the ways that emotion AI is being applied in practice and demonstrate how it has the capability to transform current procedure and systems. Equally important, however, is recognizing that certain limitations remain. This section aims to bridge the theoretical frameworks discussed earlier (Sects. 2, 3 and 4) with the tangible realities of practical application, thereby highlighting both the significant value and inherent constraints of current emotion AI technology.

5.1 Healthcare: Mental Health Screening and Therapy

An AI neural network utilized within the healthcare sector to enhance mental health outcomes is classified as emotion AI, with a particular focus on conditions such as depression, anxiety, and PTSD. For example:

- **Screening:** The data collected by wearable cameras (e.g., Fitbit) is analyzed in terms of physiological indicators (heart rate variability, sleep patterns) and vocal indicators (tone, pauses) to indicate the first signs of distress. A 2023 study found that such systems detected 78% of depression cases in clinical trials, enabling proactive intervention.
- **Therapy:** Chatbots like Woebot use NLP to engage users in cognitive behavioral therapy (CBT). By recognizing text-based cues of sadness ("I

can't get out of bed") or anger ("My boss is unfair"), Woebot tailors responses to validate emotions and teach coping strategies [10, 31].

Why It Works: Emotion AI processes data faster than humans, scaling support to underserved populations (e.g., rural areas with limited therapists).

Limitations: Cultural differences in emotional expression (e.g., stoicism in East Asian communities) lead to false negatives. Additionally, over-reliance on AI may reduce human empathy—a core component of therapy.

5.2 Retail and Marketing: Personalized Experiences

Retailers use emotion AI to optimize customer interactions and drive sales. Examples include:

- **Customer Service:** Chatbots (e.g., Sephora's virtual assistant) analyze text and vocal cues to gauge frustration. If a user says, "I've been waiting an hour!" the bot escalates to a human agent, improving satisfaction.
- **Marketing:** Brands like Netflix and Spotify use sentiment analysis to recommend content. Netflix tracks viewing habits (e.g., binge-watching sad dramas) and adjusts thumbnails to match mood (e.g., a tearful scene for a "sad" user).

Why It Works: Emotion AI turns passive browsing into personalized engagement, increasing conversion rates by 20–30%.

Limitations: Over-personalization can feel intrusive (e.g., a bot asking, "Are you stressed about work?" mid-shopping trip). Moreover, bias in training data (e.g., associating "aggressive" tones with male customers) may alienate segments of the audience.

5.3 Education: Adaptive Learning and Student Engagement

Educators leverage emotion AI to create responsive learning environments:

- **Adaptive Tutoring:** Platforms like Duolingo use NLP to detect confusion (e.g., repeated incorrect answers) and adjust lesson difficulty. If a student struggles with Spanish grammar, the system slows pace and adds explanatory videos.

- **Classroom Monitoring:** Some schools trial emotion-recognition cameras to monitor student attention. A pilot program in Texas found that alerting teachers to distracted students reduced off-task behavior by 40%.

Why It Works: Emotion AI addresses individual learning gaps, making education more inclusive for neurodiverse students (e.g., autism spectrum disorder).

Limitations: Privacy concerns dominate—parents and educators worry about constant surveillance. Additionally, overemphasis on “engagement” (e.g., rewarding compliance over curiosity) may stifle creativity.

5.4 Entertainment: Gaming and Virtual Agents

Emotion AI powers immersive experiences in gaming and virtual reality:

- **Non-Player Characters (NPCs):** Games like *The Last of Us Part II* use advanced AI to make NPCs react realistically to player emotions. If a character sees the player crying, they may offer comfort (“It’ll be okay—we’ll figure this out together”).
- **Virtual Influencers:** Avatars like Lil Miquela use synthesized speech and facial expressions to engage millions of followers. Their “emotional” responses (e.g., laughing at jokes, expressing gratitude) blur the line between fiction and reality.

Why It Works: Emotion AI makes virtual worlds feel alive, increasing player immersion and loyalty.

Limitations: The “uncanny valley” phenomenon—where near-human AI appears unsettling—can disrupt immersion. For instance, a non-player character (NPC) with stiff movements or a tone mismatch may pull users out of the experience entirely.

5.5 Key Limitations and Trade-Offs

In our analysis, we argue that while emotion AI offers significant potential benefits, its broader adoption is constrained by four critical challenges.

First, we examined data privacy concerns. The reason this is a challenge is because the collection of sensitive biometric data and behavioral information raises substantial ethical questions. For instance, we looked at a

2023 study which found that 68% of consumers are hesitant to share emotion-related data, primarily due to privacy apprehensions.

Second, we considered bias and fairness problems, explaining that emotion AI systems inadvertently reinforce injustice when training data reflects societal prejudice. For instance, we discussed a hiring algorithm that prioritizes aggressive speech tones, which might unintentionally disadvantage capable female job applicants.

Third, we examined the issue of context ambiguity, by which we meant that emotion AI is often at a loss to interpret situational nuances correctly. It is possible, for example, that an AI robot will misinterpret mourners' expressions of sorrow as evidence of deep depression, leading to unnecessary or untoward responses.

Fourth, because artificially generated emotional responses often do not hold the same depth and genuineness as real human feelings, we discovered that they are not authentic. For instance, a virtual counselor's sympathy might sound unnatural or mechanical, which would erode confidence in users.

A thoughtful synthesis between creativity and ethical responsibility is needed to address these tensions. Emotion AI can promote more user involvement and expand the reach of mental health assistance, but it requires being created and applied attentively because, while it can simulate empathy, it will never be able to replace the interpersonal connection which is the core of true emotional empathy.

6 Future Directions and Open Questions

Apart from technical advancements, the future direction of emotion AI will be shaped by open practical problems and ongoing ethical dilemmas. Apart from signaling the open questions that will continue to shape the development of the field, this section highlights three large areas of research: multimodal integration, the intersection between neuroscience and AI, and ethical regulation.

6.1 Advancements in Multimodal Emotion Understanding

- Future affective AI systems aim to combine numerous sources of data to have a better and more precise knowledge of human emotions, as

opposed to present systems that primarily draw from individual, discrete modalities (e.g., facial recognition only). For example:

- **Sensor Fusion:** This approach minimizes ambiguity by integrating physiological data (e.g., heart rate), speech prosody, and facial affect. Fear may be detected by an AI system that distinguishes a furrowed eyebrow (facial), a trembling voice (vocal), and a racing heart (physiological) much more precisely than systems reliant on a single modality.
- **Contextual AI:** This can be made more accurate by combining emotion recognition with the context of the situation, for example, between a social gathering and a business meeting. Rather than understanding the subtleties of suppressed emotion, present systems might mistake a neutral face during a hard conversation for evidence of suppressed emotion.
- **Difficulties:** Multimodal data is hard to process, and it needs novel architectures (e.g., transformer-based fusion models) and enormous and labeled dataset. Additionally, synchronizing asynchronous inputs (e.g., a delayed vocal response) remains technically difficult.

Why It Matters: Multimodal AI could revolutionize fields like mental health (detecting comorbid emotions) and human–computer interaction (creating more natural virtual assistants).

6.2 Neuro-AI Integration: Modeling Emotional States in Neural Networks

We are beginning to bridge the gap between human cognition and artificial intelligence by integrating neuroscience with AI. Key initiatives include:

- **Brain-Computer Interfaces (BCIs):** Devices like EEG headsets or fMRI scanners can decode emotional states directly from neural activity. For example, a 2023 study used fMRI to predict “frustration” in gamers with 85% accuracy, paving the way for adaptive game difficulty.
- **Neuro-Inspired Architectures:** Mimicking the brain’s limbic system (responsible for emotion) in AI models. For instance, spiking neural networks—designed to replicate neuron firing—could enable AI to “feel” simulated emotions more authentically.

Challenges: Brain data is noisy and highly individualized (e.g., one person’s “happiness” neural signature differs from another’s). Scaling BCIs

for everyday use also requires miniaturization and cost reduction.

Why It Matters: Neuro-AI could eliminate guesswork in emotion detection, making systems more reliable for high-stakes applications (e.g., diagnosing depression from brain waves). It may also advance our understanding of human emotion itself.

6.3 Ethical Frameworks for Responsible Emotion AI Development

The ethical pitfalls of current emotion AI (bias, privacy, manipulation) demand proactive solutions. Future frameworks will need to address:

- **Global Standards:** Harmonizing regulations across borders (e.g., the EU's AI Act vs. the U.S.'s FTC guidelines) to prevent regulatory arbitrage. For example, banning emotion-based discrimination in hiring globally.
- **Bias Mitigation:** Mandating “bias audits” for all emotion AI systems, with penalties for non-compliance. Tools like IBM’s AI Fairness 360 could become standard, ensuring models are tested for demographic fairness before deployment.
- **Transparency:** Requiring “emotion explainability”—systems must justify their emotional classifications (e.g., “We flagged this text as ‘angry’ because it contained aggressive language and capitalization”).

Challenges: Balancing innovation with regulation. Overly strict rules could stifle research, while weak frameworks allow harm to persist.

Why It Matters: Ethical governance, not a decision, is necessary to maintain public trust. Without it, emotion artificial intelligence is likely to repeat the sins of past technologies, such as the notorious racial biases in facial recognition systems. To ensure that emotion AI serves society in an equitable way and does not reinforce existing disparities, strong governance structures—such as global law, third-party audits, and citizen-led design—are necessary.

Open Questions Shaping the Future

The development of emotion Three controversial issues will influence AI, forcing society to balance the conflict between fundamental human values and technical potential:

1. **Can AI Ever “Understand” Emotion?** Perhaps the most intimate aspect of the human condition is feeling; what constitutes sorrow to one may hold a plethora of different meanings for another. Will artificial intelligence ever continue to break emotions down into quantifiable factors, or might it transcend mere statistical modelling to truly comprehend this subjective unpredictability?
2. **Who Owns Emotional Data?** Competing rights issues arise due to the fact that emotion AI creates very intimate data, like wearables to monitor everyday mood trends. Is the platform that captures and processes emotional data its owner, or do individuals retain ownership?
3. **What Is the Line Between Help and Harm?** Emotion AI can do good for mental health services, but there are also very real dangers, including the danger of dystopian surveillance and misleading marketing. When does society need to intervene to prevent potential harm, and when should it limit its good applications?

7 Conclusion: Bridging Psychology and Technology

This chapter has explored the intricate connection between human emotion and artificial intelligence, from the psychological processes that support emotional expression and perception to the computational approaches that allow machines to detect and replicate these states. These discoveries highlight an underlying paradox: while emotion AI can potentially transform human well-being, proper use requires a systematic, morally grounded approach marked by humility and rigor (Table 3).

Table 3 Evaluation metrics for emotion AI systems

Metric type	Description	Application domain	Example tools/methods
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Metric type	Description	Application domain	Example tools/methods
Objective metrics	Quantifiable and data-driven performance indicators that measure the technical accuracy or efficiency of a model	Text and speech synthesis systems	Perplexity (for NLP tasks); mean opinion score (MOS) for audio evaluation
Subjective metrics	Human-rated assessments focusing on perceived quality, emotional appropriateness, or naturalness of outputs	Applicable across all output modalities (text, speech, facial expressions, etc.)	Likert-scale surveys; pairwise comparison tests
Contextual metrics	Evaluate how well system responses align with contextual or situational norms and expectations	Chatbot conversations; virtual agent interactions	Task success rate; empathy quotient (EQ) scores
Longitudinal metrics	Assess consistency, adaptability, and emotional engagement across multiple sessions or prolonged interactions	Embodied conversational agents; social and companion robots	User retention statistics; willingness for repeated interaction

Synthesis of Key Themes

This chapter begins by situating emotion AI in psychological context, emphasizing the necessity of understanding fully human emotions, their biological foundation and their cultural differences, so that we are not misreading the signals AI is reading. Then, in Sect. 2, we examined how AI reads these signals and generates its own emotional responses. In Sect. 3, we concluded that while robots may mimic expressions of emotion, they cannot replicate the embodied human experience of emotion.

Ethical concerns have always taken center stage. Issues such as privacy, bias, and manipulation are genuine hurdles to equitable use of emotion AI; they are not hypothetical (Sect. 4). This leads us to a crucial realization: emotion AI is a socio-technical system that demands balance between responsibility and creativity. To make it responsible, solving the above ethical dilemmas requires surmounting challenging real-world hurdles.

Emotion AI's revolutionary potential and accompanying issues were illustrated through real-world uses like individualized marketing and mental health screening (Sect. 5). To further develop the field in the future, concerted efforts will be required in three areas (Sect. 6): applying knowledge from neuroscience, establishing robust ethical governance and

legislation, and combining different types of data through multimodal approaches.

The Interdisciplinary Imperative

Emotion AI is not exclusively a technical endeavor; it is fundamentally a sociotechnical system. Psychology elucidates the nature of emotions, while artificial intelligence supplies the mechanisms to interact with them. But to avoid replicating human biases or creating new harms, we must embed psychological and ethical expertise into every stage of development. For example:

- A mental health bot designed without input from therapists may prioritize speed over empathy.
- A hiring algorithm trained on biased historical data will perpetuate inequality.

These examples underscore a simple truth: emotion AI is only as responsible as the humans who build it.

A Call to Action

The future of emotion AI is not predetermined. It will be shaped by the choices we make today:

- **For Developers:** Prioritize transparency (e.g., explaining why an AI flagged “anger” in a text) and bias mitigation (e.g., diverse training data).
- **For Policymakers:** Create agile, global regulations that balance innovation with protection (e.g., banning emotion-based discrimination).
- **For Society:** Engage in public discourse about the role of AI in emotional life—what we value, what we fear, and what we will not tolerate.

Emotion is the essence of human connection. As we hand over parts of this connection to machines, we must ensure that AI augments, rather than replaces, our capacity for empathy. The path forward is not easy, but it is necessary. By bridging psychology and technology with intentionality, we can build a future where emotion AI serves humanity—not the other way around.

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Theories of Emotions in Psychology

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Abstract

This chapter explores various theories within psychology to understand emotions, focusing on both Western and Indian perspectives. Western theories based on contributions by Darwin, James-Lange, Cannon-Bard, Schachter-Singer, Ekman, etc. are discussed. These theories are classified as Evolutionary, physiological, cognitive, constructivists, and socio-cultural in their approach. Indian psychological frameworks for Emotions explore Bharatamuni's Rasa theory in Natyashastra, emotional management as mentioned in the Yoga Sutras of Patanjali, Buddhist emotional classifications, and Panch kosha models. A comparative analysis highlights epistemic and ontological differences, contrasting the Western emphasis on biology and cognition with Indian models' spiritual and aesthetic orientations. The chapter advocates for an integrative, culturally sensitive and holistic approach to emotional theory that enriches global psychological understanding and practice. This chapter also discusses application of various emotion's theory in therapeutic and forensic setting.

Keywords Emotion – Indian psychology – Western psychology – AI and emotions

1 Introduction

One time or another, we all may have experienced some level of emotional arousal or emotional outburst followed after either a positive or negative life event. Emotions act like fundamental part or building blocks of the human experience. Emotions shape nature of our relationships, influence decisions, and sense of self. Emotions give colour, meaning to our lives and experiences. Yet, for generations psychologists have been intrigued about science of emotion or from where do these emotions come or unfold and hence study them. Emotions as a term is very widely used but formally defining term in universally accepted manner seems to be elusive task. Word emotion is derived from Latin word “emovere” which means “to move, move out, or move through or to stir”. Many psychologists have worked towards understanding or defining the term. One of the common understandings of ‘Emotion’ refers it to “feelings that generally have both physiological and cognitive elements and that influence behavior.” [35]. Emotions can be viewed as a complex reaction to some internal or external stimuli and it involves physiological and behavioral reactions along with facial expressions, thoughts, and affective responses. Emotion includes feeling, thinking, activation of the nervous system, bodily changes, and behavioral changes such as facial expressions, Thus, emotions can be viewed as combination or mix of three things, (1) physiological arousal, (2) expressive overt behavior, and (3) conscious thoughts or cognitions and feelings accompanying cognitions. There are two different contradicting views concerning interplay of these three components of emotions viz., does physiological arousal precede our emotional experience or cognitions precede emotions. Theorists are debating over the view of whether emotional response predominate cognitive processes or response or it is vice versa. Even though continuing debate about sequence, there is general agreement on emotions being made up of three parts: subjective experiences, physiological responses and behavioral responses.

1.1 Significance of Emotions in Human Experience and Psychology

Psychology is scientific study of Human Behavior. Studying emotions aids in understanding human behavior, cognitions and social interaction. It helps in get an insight into mental health, decision-making processes,

interpersonal communications, and the biological underpinnings of affective states. Understanding human emotions or being emotionally intelligent is important as it helps in attainment of psychological wellbeing, social success, and helps in management of emotions as well [105]. Additionally, a deeper understanding of emotions facilitates developing therapeutic interventions and improving emotional regulation across populations.

The perception of the surroundings and how individuals interact with the world around them is shaped by emotions. In the case of nature of social relationships, motivation and even decision making, emotions play an important role [35]. Emotion provides essential information about events occurring in our environment and thus helps in preparing for adaptive responses, and makes social responses in a way that is constructive for social bonding [27]. In the view of [77], depth and meaning of human experience greatly depends on emotions.

1.2 Definition and Components of Emotions

Emotions have numerous aspects related to them, they are many things at once, hence there seem to exist many definitions of Emotions. Kleinginna and Kleinginna [54] listed around 92 definitions of emotions and summarised that, to define Emotions more appropriately below 5 pointers need to be addressed:

- (1) something about feeling when we are emotional;
- (2) physiological or bodily aspects of emotional feelings;
- (3) effects of emotions on perception, behavior, thoughts;
- (4) properties of emotions to drive or motivate certain behavior;
- (5) expression of emotions by the means of language, facial expression and/or gestures [77].

American Psychological Association (APA) defines Emotion as “a complex reaction pattern, involving experiential, behavioral, and physiological elements, by which an individual attempts to deal with a personally significant matter or event. The specific quality of the emotion

(e.g., fear, shame) is determined by the specific significance of the event. Emotion typically involves feeling but differs from feeling in having an overt or implicit engagement with the world” (“APA dictionary of psychology,” 2019). Oxford English Dictionary (1996), defined Emotions as “a strong mental or instinctive feeling such as love or fear involving many bodily processes, and mental states”. Thus, Emotions can be understood as psychological state involving below 4 essential components

- (1) Physiological Arousal—bodily reactions like palpitation, increase in heartbeat, flight or fight responses, hormonal changes facial expressions etc. [54].
- (2) Subjective feelings—subjective awareness, or conscious experience or ‘feeling’ that may be positive or negative [35].
- (3) Cognitive Processes—activation of specific mental processes or information; a person’s perceptions, expectations and interpretations [60, 61].
- (4) Behavioural reactions—overt behavioral reactions or actions (flight, fight or freeze responses) or expressions, such as gestures, vocal tone, or facial movements, that communicate emotions to others [27].

These components interact dynamically, contributing to the richness and variability of emotional experiences [79].

1.3 Overview of Universal Emotions and Cultural Influences

Emotional reactions occur instinctively, suggesting we do not actively try to experience them; rather, they emerge with ease. Of all the emotions that humans undergo, there are seven universal emotions—happiness, sadness, anger, fear, astonishment, and disgust—that are shared by all people and go beyond the boundaries of language, culture, and ethnicity [29]. However, cultural norms influence the expression and regulation of emotions through display rules, which stipulate social and cultural contexts [69, 121]. These influences show how we differ in the expression of emotion and emphasize the need to understand the sociocultural dimension of emotion [79].

1.4 Aim and Scope of the Review

The goal of this chapter is to critically analyze the development of psychological theories of emotions from classical to modern integrative frameworks, offering a thorough and up-to-date account. It examines some of the major Western theories of emotions in conjunction with Indian philosophical perspectives in order to construct a more holistic account of emotions that synthesizes scientific understanding, culture, and lived experience. The chapter also covers applications in forensic psychology and newer AI trends in emotion research. It is hoped that this interdisciplinary framework will enrich the understanding of emotions and help stimulate more culturally informed and scientifically rigorous research.

2 Historical Overview and Foundations of Emotion Research

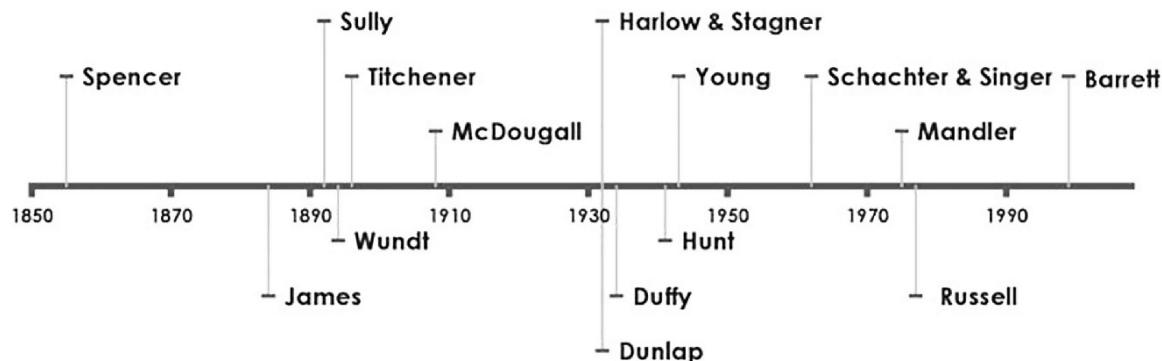
2.1 Early Perspectives and Key Milestones in Emotion Research

Diverse theoretical and empirical researches in over more than a century have led to evolution of the scientific study of emotions. Earlier researches were focused on identifying biological and psychological foundations of emotions and that laid the foundation for modern psychological inquiry. The study of emotions initially combined observations from physiology, evolutionary biology, and introspection, which marked a multidisciplinary approach that has persisted even in current times [37]. Gendron and Feldman Barrett [37] in their research paper titled “Reconstructing the Past: A Century of Ideas About Emotion in Psychology” provided a comprehensive historical account of the scientific study of emotion in psychology. Paper discusses three important approaches towards researching or theorising emotion in psychology namely, Basic Emotion, Appraisal, and psychological constructionist approach [37].

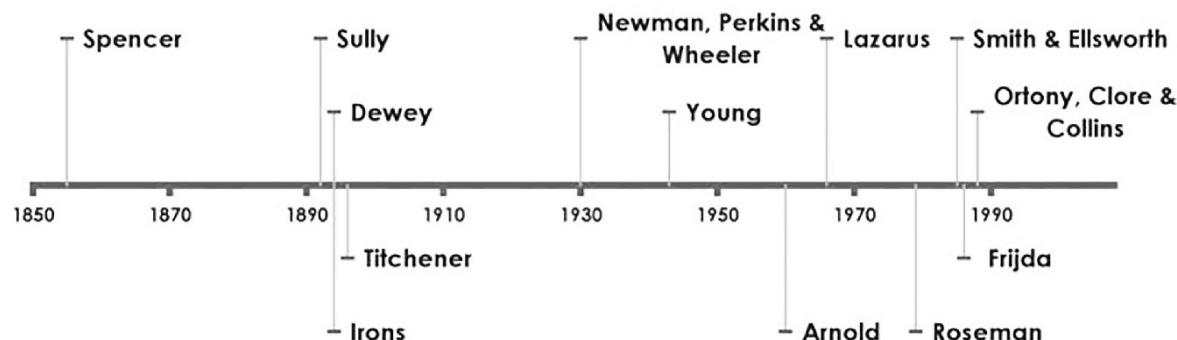
- Basic Emotion approach stated that Emotions are biologically hardwired, universal in nature and produce stereotypical expressions and physiological responses.
- Appraisal Approach proposed that Emotions arise from an a person’s interpretation or appraisal of events, emphasizing the role of meaning-making.

- Psychological Constructionist Approach states that Emotions are constructed from more fundamental psychological components (like affect and cognition) that are not specific to emotion itself. This approach explains the variability in emotional experiences and expressions, which the other two approaches address only superficially (Fig. 1).

Psychological Constructionist Theorists



Appraisal Theorists



Basic Theorists

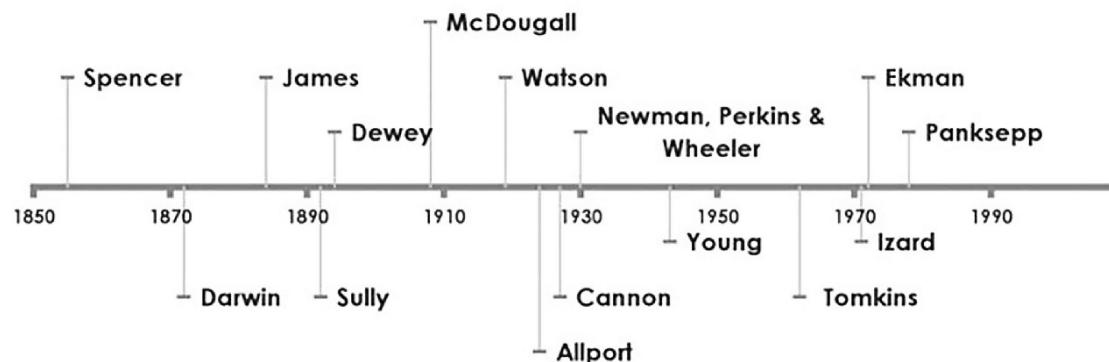


Fig. 1 Summarising key researchers from three distinct timelines in three approaches to study of emotion. [37]

Source Gendron and Feldman Barrett

2.2 Darwin's Evolutionary Theory of Emotion (Golden Years)

Charles Darwin's pivotal work, *The Expression of the Emotions in Man and Animals* (1872), was a pioneering contribution that proposed emotions have an evolutionary basis. Darwin argued that emotions evolved to serve adaptive functions crucial for survival and reproduction, such as fear triggering fight-or-flight responses [21]. He emphasized that emotional expressions are universal and conserved across species, providing a biological continuity between humans and animals [27]. Darwin's theory laid the groundwork for later research focusing on emotions as innate and biologically hardwired phenomena.

2.3 William James and Carl Lange's Contributions

At the advent of the twentieth century, William [48] and Carl Lange put forth James-Lange theory of emotion. They proposed that emotions arise from the perception of physiological changes in the body and not the other way around [48, 59]. It states that an external stimulus in environment triggers a bodily reaction, and the brain interprets these physiological responses leading to experience of a specific emotion. This theory shifted the focus toward the body's role or rather brain's interpretation of physiological reactions in emotional experience and it also influenced consequent physiological models of emotion [56].

2.4 Behaviorism and Its Impact on Emotion Research (the “Dark Ages”)

The subsequent “Dark Ages” (circa 1900–1960) saw emotion research sidelined by behaviorism, though important neurobiological work persisted. Owing to dominance of behaviorism, focus was more on observable behaviors and not on internal mental states as objects of research. Study of emotions was often dismissed as being subjective experience or unmeasurable phenomenon [37].

2.5 Renaissance of Emotion Research in the 1960s and Onward

The 1960s marked a renaissance in research of emotions which was driven by cognitive psychology and neurobiology. Magda Arnold's appraisal model emphasized the role of cognitive interpretation of events being

central to emotional experience [1]. Sylvan Tomkins revived the basic emotion view [120] However, this basic emotion–appraisal dichotomy had overshadowed a third, psychological constructionist tradition, which viewed emotions as constructed from more fundamental psychological components. Recent scholarship highlights the need to recognize this neglected tradition for a fuller, more accurate account of emotion research in psychology.

During this era of renaissance also contributed to emergence of prominent theories of emotions like Schachter and Singer's two-factor theory (1962), and Lazarus' cognitive appraisal theory [60], which integrated both physiological and cognitive components. This resurgence recognized emotions as a legitimate focus of scientific investigation. It also encouraged multidisciplinary approaches to understand emotions using psychology, neuroscience, and anthropology [37].

2.6 Summarizing Major Research Eras

Emotion research can be broadly categorized into three historical eras:

- Golden Years (1855–1899): Characterized by foundational work from Darwin and James, focusing on biological and physiological bases of emotion [21, 48].
- Dark Ages (1900–1959): A period of decline in psychological emotion research due to the rise of behaviorism, which marginalized internal emotional states [125].
- Renaissance (1960–Present): Renewed focus on cognitive and neurobiological mechanisms of emotion, with integration of appraisal theories and recognition of emotions as complex psychological phenomena [37].

3 Physiology and Neuroscience of Emotions

3.1 Role of the Autonomic Nervous System (ANS)

The Autonomic Nervous System (ANS) plays a pivotal role in the physiological underpinnings of emotions by regulating involuntary bodily functions in response to emotional stimuli. The ANS mediates bodily changes such as heart rate, respiration, and hormonal secretion that prepare the organism for adaptive reactions like fight, flight, or freeze [14]. These

autonomic responses are critical components of emotional arousal and form the physiological basis upon which emotional experiences are built.

The ANS is divided into two branches—the sympathetic nervous system (SNS) and the parasympathetic nervous system. The sympathetic branch typically initiates arousal during emotionally charged situations, while the parasympathetic branch facilitates calming and recovery processes [57]. During stressful or emotional arousing event, the sympathetic nervous system activates the “fight-or-flight” response. This leads to increasing heart rate, dilating pupils, and redirecting blood flow to muscles to prepare the body for action. While, the parasympathetic nervous system supports the “rest-and-digest” state, which promotes relaxation and recovery after emotional arousal [113]. These physiological changes form the bodily sensations are often associated with different emotions, for e.g., a racing heart in fear or a calming breath in relief. The ANS also communicates with the brain, mainly emotion-related areas like the amygdala and prefrontal cortex. This allows for feedback which shapes emotional awareness and regulation [113]. Dysregulation of the ANS has been linked to emotional disorders like anxiety and depression. Thus, the ANS plays a crucial role, and is not just reactive but integrally involved in shaping, experiencing, and regulating emotions.

3.2 Key Brain Areas and Neural Networks Involved in Emotion

To understand neurobiological underpinnings of emotions better, one need to understand neural mechanisms too. This includes interconnected brain structures and neurotransmitter system [113]. Emotional processing contains a complex network of brain regions, and the amygdala is regarded as central to detecting and assigning emotional significance to sensory inputs. The amygdala, often known as *emotional brain*, is central to emotion theory. It assesses sensory information and gives emotional qualities or meaning to those sensory inputs. Amygdala adjusts autonomic and endocrine functions, along with decision-making, and regulating instinctive behaviors. The amygdala integrates sensory information and orchestrates responses to threats or rewards, influencing both behavioral and physiological reactions [62, 92]. The amygdala becomes more active with negative emotions like anger or fear, and less active with positive

emotions like love. Any dysfunction or damage to amygdala can lead to problems in controlling emotions, specially fear and aggression [113].

The thalamus functions as a relay centre, transmitting sensory information to cortical and subcortical areas and coordinating rapid emotional responses [14]. The hypothalamus regulates physiological expressions of emotion such as hormonal release, autonomic activation, and homeostatic balance [106]. Higher cortical areas i.e. regions like the ventromedial and anterior cingulate cortices in the prefrontal cortex are involved in conscious emotional experience, decision making and cognitive appraisal of stimuli [83, 92]. According to current research emotions originate from dynamic, large-scale networks rather than being restricted to a particular area of the brain. These networks integrate perception, cognition, and bodily states. It thus reflects that both innate and learned components of emotional life [92, 113]. Integrative systems that connect perception, thought, and physical states are formed by large-scale networks such the limbic system and prefrontal cortical areas [92]. The amygdala and anterior insula are part of the salience network, which recognises emotionally charged stimuli and promotes quick reactions [112]. According to Buckner et al. [12], the executive control and default mode networks support the cognitive evaluation and control of emotions. According to Barrett, these overlapping networks allow emotions to be adaptable, context-sensitive, and impacted by past experiences and education.

3.3 Interaction Between Physiological and Cognitive Components

Emotional experiences arise from both—the interplay between bottom-up physiological signals and top-down cognitive processes. Subjective emotional feelings get shaped by the brain's cognitive interpretation of raw affective data that is provided by physiological arousal that ANS and subcortical brain generates [60, 61, 108]. This interaction between various bodily functions allows emotions to be both reactive and reflective. This is achieved by integrating sensory input along with memory, expectations, and cultural context. For example, two individuals may show similar physiological arousal but at the same time experience different emotions. This individual difference comes from how one appraises and labels the situation cognitively [108]. This Understanding of bidirectional influence explains the variability and complexity of human emotional life.

4 Major Psychological Theories of Emotions

4.1 Evolutionary Theory

The evolutionary approach to emotions was pioneered by Charles Darwin and later William McDougall expanded same. Emotions are believed to be adaptive mechanisms that are shaped by natural selection and enhance survival and reproductive chances. Darwin asserted that emotions serve functional purposes i.e. signalling danger, or facilitating social bonding, and motivating appropriate behavior to meet environmental challenges.

McDougall [72] further emphasized the instinctual basis of emotions.

Evolutionary approach states emotions are universal and are biological hardwired. This evolutionary continuity is observed across species [21, 72].

4.2 Physiological Theories

(a) James-Lange Theory

William James and Carl Georg Lange, proposed similar ideas independently, and now are recognised as James-Lange theory of Emotions. This theory proposes that emotions are caused by our interpretation of bodily reactions to events. In other words, physiological arousal or action precedes emotions we feel. How one interprets the bodily reactions to stimuli will determine the type of emotion we would feel [48, 59]. This theory highlights the centrality of bodily feedback in emotional experience, suggesting a causal sequence from physiological arousal to emotional feeling [56] (Fig. 2).

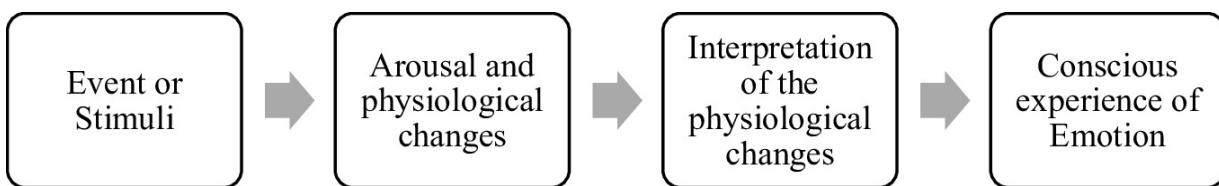


Fig. 2 James-Lange theory of emotion.

Source [56], p. 262]

Critics for this view point suggest that theory was based on introspection and correlational research, rather than controlled experiments. Hence, cannot be verified or generalised. Also, it put too much emphasis on

bodily signals, when evidence suggest emotions can exist before physiological arousal too [56].

(b) Cannon-Bard Theory

In criticism to James-Lange theory, Walter Cannon and Philip Bard, proposed second major theory named Cannon-Bard theory. This theory views that emotions and physiological reactions occur simultaneously and independently. It also suggested that Emotions can be experienced even in absence of bodily reactions or physiological arousal. Theory indicates that when a stimuli or event is presented to us, our nervous system coordinates prompt and simultaneous response of body's instinctive reaction and mind's emotional perception or interpretation. It states our thalamus plays a crucial role in the same, hence many a times this theory is viewed as thalamic theory of emotions [2, 14]. Cannon-Bard theory contests the idea that bodily changes alone determine emotion. It emphasizes parallel processing in the brain [79] (Fig. 3).

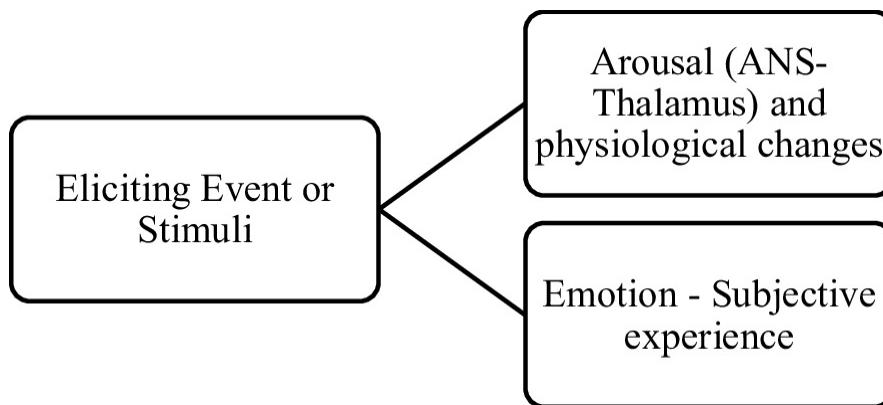


Fig. 3 Cannon-Bard theory of emotion.
Source Summarised by author (2025)

4.3 Cognitive Theories

(a) Schachter-Singer Two-Factor Theory

Theory of Emotion proposed by Schachter-Singer is a two-factor theory which proposes a specific emotional state is produced by the combination of physiological arousal along with cognitive interpretation of the same or

'labelling' of the stimulus or event. Two factors on which emotion elicitation depends on are—(1) a state of general autonomic arousal, and (2) second cognitive interpretation or 'label' that describes the experience. This theory accounts for individual difference in emotional experience as it is based on contextual interpretation of environmental stimuli [81, 108] (Fig. 4).

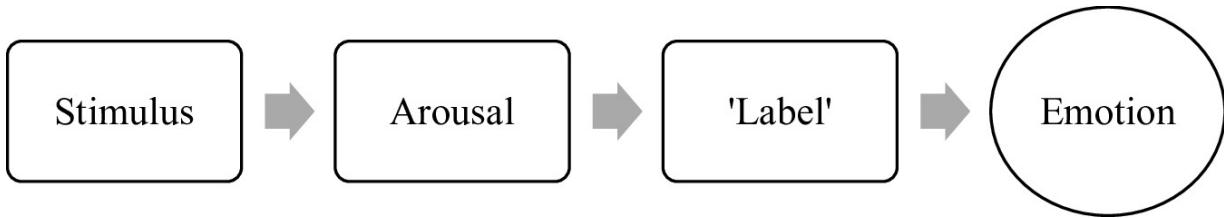


Fig. 4 Schachter-Singer two-factor theory.

Source [81]

(b) Lazarus' Cognitive Appraisal Theory

The cognitive appraisal theory by Lazarus [60] suggest that our brain first appraises a situation, stimulus, or event and the resulting response from that appraisal is an emotion. There are two levels of appraisals—primary and secondary. Primary appraisal refers to interpretation of the stimulus or event which can be positive or negative and secondary appraisal refers to analysis of resources and our response or reaction. Every emotion has a 'core relational theme' of individual relating to the situation. This core relational theme refers to underlying meaning person assigns to stimulus which triggers a specific emotion. The relationship between the person and environment act as important contributing factors in emotions and this core relational theme [37, 60, 61] (Fig. 5).

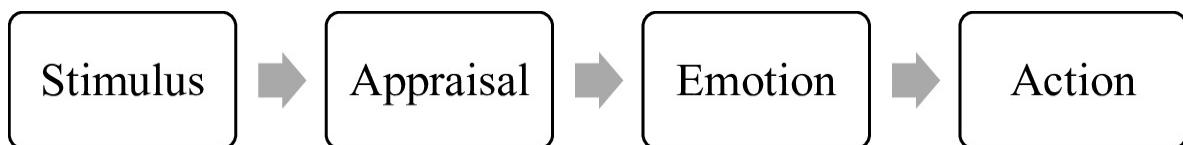


Fig. 5 Lazarus cognitive appraisal theory.

Source Summarised by author (2025)

4.4 Constructivist Theory

Lisa Feldman Barrett's theory of constructed emotion (2017) challenges traditional views of emotions as innate, discrete entities. Alternatively, Barrett argues that emotions are dynamically constructed by the brain through a process that integrates three components viz., internal bodily sensations-signals, prior experiences, and cultural concepts. Emotions are dependent on context. They are shaped by learning and individual differences, rather than being fixed biologically hardwired. This theory highlights predictive and interpretative role the brain plays in forming emotional experiences. It also accounts for the variability observed across cultures and individuals.

Theory proposes that emotions are constructed by brain using predictions based on past experiences. Brain keeps continuously creating internal models to predict and interpret sensory inputs and bodily states, and not react to stimulus or world around, which helps adjusting behaviour to maintain *allostasis*. Allostasis refers to the proactive regulation of bodily systems to ensure survival and balance. Thus, emotions like fear or anger are not tied to specific brain area but are mental categories individual creates from cultural, social, and personal experiences. Emotional episodes occur when the brain interprets internal and external stimuli as fitting a specific emotional concept. For e.g., people with amygdala damage can also experience or recognize fear under certain conditions. This shows that emotions are not dependent on single brain structures [113].

Emotions, thus, originate from the brain's *predictive coding process* which matches predictions to sensory input and adjusting as needed. Emotions are shaped over time and vary across cultures. In infants, bodily states exist before emotions; only when the brain matures enough to make detailed predictions do emotional experiences arise. This theory challenges traditional views by emphasizing the brain's role in constructing emotions from top-down processes [113]. Let us understand same taking an example. Say there is a psychology research scholar aged 26 attending a international conference and presenting a research paper for the first time. She notices her heart racing, palms sweaty, and butterflies in stomach. A classical view of emotion would suggest that these physiological responses would be interpreted as feeling emotion i.e. fear which is an automatic, hardwired response to stressful situation of public speaking. From Barrett's theory perspective, it would be understood as her brain receiving signals from her body and comparing same with her past experiences. Based on context,

social norms, her cultural understanding, her brain might construct the emotion of anxious anticipation and not fear.

4.5 Social and Cultural Theories

(a) Paul Ekman's Theory of Universal Emotions and Cultural Display Rules

Paul Ekman and Wallace Friesen, on the basis of their studies concluded that six types of basic emotions exist universally namely, surprise, happiness, anger, fear, disgust, and sadness [56, 79]. Each of these universal emotions has unique signals, physiological responses, and timelines.

Although the onset, duration, and decline may differ. There exists some level of similarities as well as difference in how emotions are experienced and expressed across various cultures and across gender. ‘Display rule’ that are part of each culture determines how emotions are expressed appropriately and these in turn set gender expectations of emotional experience and expression. Display rules refer to customs or social norms which are used to regulate emotional expression in a given culture [79].

(b) Cultural-Historical Activity Theory (CHAT) by Vygotsky and Leontiev

L. S. Vygotsky and Aleksei N. Leontiev founded Cultural-historical activity theory (CHAT). It is a theoretical framework to conceptualise and analyze relationship between cognition and action. It views human activity as a dynamic, socially and culturally influenced process. CHAT views emotions as a phenomenon embedded in human activities and mediated by social and cultural factors. Since emotions develop via culturally meaningful activities and internalization of social norms, one cannot separate emotions from cultural practises and social interactions [63, 124]. CHAT highlights how emotions are dynamic and developing, and how language and culture shape emotional experiences and regulation [33].

5 Integrative Comparative Summary of Theories

5.1 Comparative Overview of Major Emotion Theories

See Table 1.

Table 1 Comparison and summarization of key aspects of each psychological theory

Theory	Origin of emotion	Brain mechanisms	Role of culture	Expression of emotion
Evolutionary theory	Innate, biologically hardwired	Limbic system (amygdala, hypothalamus)	Minimal; emotions are universal	Universal facial expressions [21, 27]
James-Lange theory	Bodily physiological changes	Peripheral nervous system signals	Minimal	Body-driven, physiological cues
Cannon-Bard theory	Simultaneous brain and body responses	Thalamus coordinating parallel responses	Minimal	Simultaneous physiological and subjective
Schachter-Singer two-factor	Interaction of arousal and cognition	ANS arousal plus cortical appraisal	Moderate; labeling influenced by context	Expression depends on cognitive labeling [108]
Cognitive appraisal theory	Cognitive evaluation of stimuli	Prefrontal cortex and limbic system	High; appraisal shaped by environment and culture	Expression shaped by appraisal outcomes [60, 61]
Constructivist theory	Constructed through experience and culture	Distributed brain networks; predictive processing	Central; culture and experience shape emotion	Highly variable, context-dependent
Social-cultural theories (Ekman, CHAT)	Socially mediated and culturally shaped	Neural circuits modulated by social context	Fundamental; culture shapes emotional norms and display rules	Expression governed by social norms and learned rules [27, 124]

Source Summarised and compiled by authors (2025)

5.2 Strengths and Limitations of Each Theory

- Evolutionary Theory

Strengths: Explains universality and adaptive functions of emotions; supported by cross-species evidence.

Limitations: May underplay cultural variability and cognitive complexity [[27](#), [37](#)].

- James-Lange Theory

Strengths: Emphasizes bodily feedback and physiological correlates.

Limitations: Difficult to explain emotions without distinct physiological patterns; lacks evidence for causal order [[56](#)].

- Cannon-Bard Theory

Strengths: Accounts for simultaneous emotional and physiological responses; supported by neuroanatomical data.

Limitations: Does not explain cognitive appraisal or variability of emotions [[79](#)].

- Schachter-Singer Two-Factor Theory

Strengths: Integrates cognition and physiology; explains context-dependent emotions.

Limitations: Ambiguity in defining cognitive labeling processes; some replication issues in experiments [[108](#)].

- Cognitive Appraisal Theory

Strengths: Highlights individual differences and role of interpretation; useful for stress and coping research.

Limitations: Complexity in measuring appraisal processes; sometimes criticized for overemphasizing cognition [[60](#), [61](#)].

- Constructivist Theory

Strengths: Accounts for cultural, contextual, and individual variability; integrates neuroscience and psychology.

Limitations: Abstract nature can challenge operationalization; ongoing debate on universality versus construction.

- Social and Cultural Theories

Strengths: Emphasizes the social context and cultural norms; explains variation in emotional expression.

Limitations: May underestimate biological bases; complex to empirically validate social influences [27, 124].

5.3 Contemporary Syntheses and Debates in Emotion Theory

In recent time, emotion researchers attempt to merge and integrate diverse theoretical frameworks. They agree and recognise that emotions are multifaceted and complex phenomenon incorporating all three biological, cognitive and sociocultural components. Barrett proposed that emotions emerge from predictive brain processes that are shaped by bodily states and cultural learning. This approach to studying emotions incorporates both physiological and constructivist approach to understanding of emotions. Likewise contemporary models of emotions highlight dynamic and distributed processing of emotion, and advocate that a single isolated region is not involved in emotions, but a large-scale brain network is involved [92].

Disagreements still exist on whether emotions are universal or culture specific. Research is ongoing to find a balance between naturally occurring emotional reactions (innate tendencies) and culturally shaped emotions [37]. The role of cognition—whether emotions come before or are created by cognitive appraisal—is another point of debate. This debate repeats earlier disagreements between the James-Lange and Cannon-Bard viewpoints, but this debate is now enhanced by contributions from contemporary neuroimaging and cross-cultural data [60, 61].

Developments in affective neuroscience and computer modelling offer new tools to understand complexity of emotions. This has pushed interdisciplinary approach which integrate both psychological theories, sociocultural insights and empirical brain data [92].

6 Indian Perspectives on Emotions

As far as ‘Emotions’ are concerned, in Indian perspective, there is more of a philosophical approach to it as compared to western theories.

6.1 Rasa Theory from Natyashastra: Aesthetic and Experiential Emotions

Emotions are viewed in the aesthetic sense as discussed in Bharat Muni's ancient Sanskrit treatise (circa 200 BCE–200 CE) 'Natyashastra' and viewed it as emotional states or 'Rasas'. Rasa, here is understood in terms of 'essence' or 'flavour' i.e. emotional response resulting from artistic performances like dance, drama or music. Western models of emotions often categorise emotions as discrete, biologically driven affective states, whereas Rasa theory views emotions as something dynamic and result of interplay between the performer, the artistic medium, and the spectator. The theory identifies nine primary rasas: "love (śṛṅgāra), laughter (hāsyā), compassion (karuṇā), anger (raudra), valour (vīra), fear (bhayānaka), disgust (bībhatsa), wonder (adbhuta), and tranquillity (śānta)" [16]. Theory posits that each Rasa originates from a 'sthayi bhav' i.e. a stable emotion. This rasa experience is heightened by 'vibhavas'-stimuli or determinant, 'anubhavas'-expressions or consequents, and 'vyabhicharibhavas'- temporary emotions or transitory states [9, 16]. Recent neuroscientific research conducted by Pandey et al. [88] has found that distinct neural signatures exist for each rasa. This finding demonstrates that particular brain oscillations—especially in the delta, beta, and gamma frequency bands—discriminate between the emotional states elicited by different rasas [88]. Rasa theory integrates psychological and social mechanisms through which personalised emotions are universalised and focus on empathy, aesthetic experiences and specific role of audiences. Rasa theory offers rich, diverse, cross-cultural insights into the nature of emotions and it also emphasises the transformative power which art provides to harmonize and elevate emotional experiences. Rasas give spiritual and psychological understanding and are experienced together. Rasa theory promotes empathy and a sense of interconnection by emphasizing the transforming and shared influence of emotions in art. In contrast to Western paradigms, Rasa theory put forth a unique viewpoint on psychology by combining the cognitive, expressive, and cultural dimensions of emotion. Western theories concentrate on distinct emotions, whereas Rasa theory advocates universal experience of emotions which promotes emotional transcendence and aesthetic satisfaction.

6.2 Pancha Kosha Theory: Layers of Human Existence and Emotions

The origins of Pancha Kosha theory, can be found in the *Taittiriya Upanishad* within Indian Knowledge systems of Vedas. By the means of five interwoven sheaths or ‘Koshas’, Panch kosha theory provides a comprehensive framework to comprehend human personality and emotions. Koshas are covering of the atman or layers of human existence. From the material physical body to the delicate spiritual core, each of these kosa’s functions as an inner layer of existence. It highlights how the body, mind, and soul are all interconnected. “Annamaya Kosha, Pranayama Kosha, Manomaya Kosha, Vigyanamaya Kosha, and Anandamaya Kosha” are the five sheaths, or Koshas. The physical or tangible body is referred to as Annamaya Kosha; the vital life force or breath is called Pranayama Kosha; the mental, psychological, or emotional state is called Manomaya Kosha; the intellectual or wisdom component is called Vigyanamaya Kosha; and the state of endless liberation or pure happiness is called Anandamaya Kosha. Contrary to Western trait-based models, in this theory, personality is viewed as dynamic, and capable of transformation through practices like yoga and meditation, aiming for self-realization and eternal bliss [87, 107]. Emotions are seen to be related to Manomaya Kosha or the mental sheath. Manomaya Kosha includes feelings, cognitions, desires. Feeling which are Ego-driven like pride, jealousy, etc. can upset the equilibrium in this sheath and can result in physical disease i.e. *Vyadhi* and tension i.e. *Adhi*. Emotional control, balance or harmony can be achieved by cleaning Manomaya kosha with yogic techniques like meditation, breathing exercises and ‘*Satvavajaya Chikitsa*’ which is Ayurvedic psychotherapy. *Satvavajaya Chikitsa* is one of the *Trividha Chikitsa* or threefold treatment frameworks given by Charaka in Ayurveda. *Satvavajaya Chikitsa* mainly focuses on treating mental illness or psychiatric disorders, especially psychosomatic disorders where mind is affected. *Satvavajaya Chikitsa* is correlated to the modern medical treatments like psychotherapy and Cognitive behavioural therapy (CBT). Aim here is to re-establish normal mental activities by creating balance in mind using religious or regular practise of Yama, Niyama, and Pranayama. *Satvavajaya Chikitsa* is non-pharmacological approach to manage mental disorders and balance rajas, and tamas doshas of mind [100].

While the Anandamaya Kosha symbolises a state of perfect happiness that transcends transient emotions, the Vigyanamaya Kosha, which governs intellect and discernment, further refines emotional responses by fostering wisdom [87]. This theory suggests that emotions are not just confined to the brain. They span physical sensations (as in Annamaya kosha), energetic shifts i.e. pranayama kosha, mental interpretation which is manomaya kosha, wise evaluation or intellectual description as in Vigyanamaya kosha and emotional well-being at deeper level which is Anandamaya kosha. Theory postulates that effective emotional regulation needs working through all the five layers or koshas from controlling breathing to cognitive restructuring or reframing to cultivating state of bliss. Emotional imbalances or dysregulation is viewed as disruptions across these koshas, suggesting that emotional regulation can be achieved by integrating approaches that involve body, mind, and spirit (Fig. 6 and Table 2).

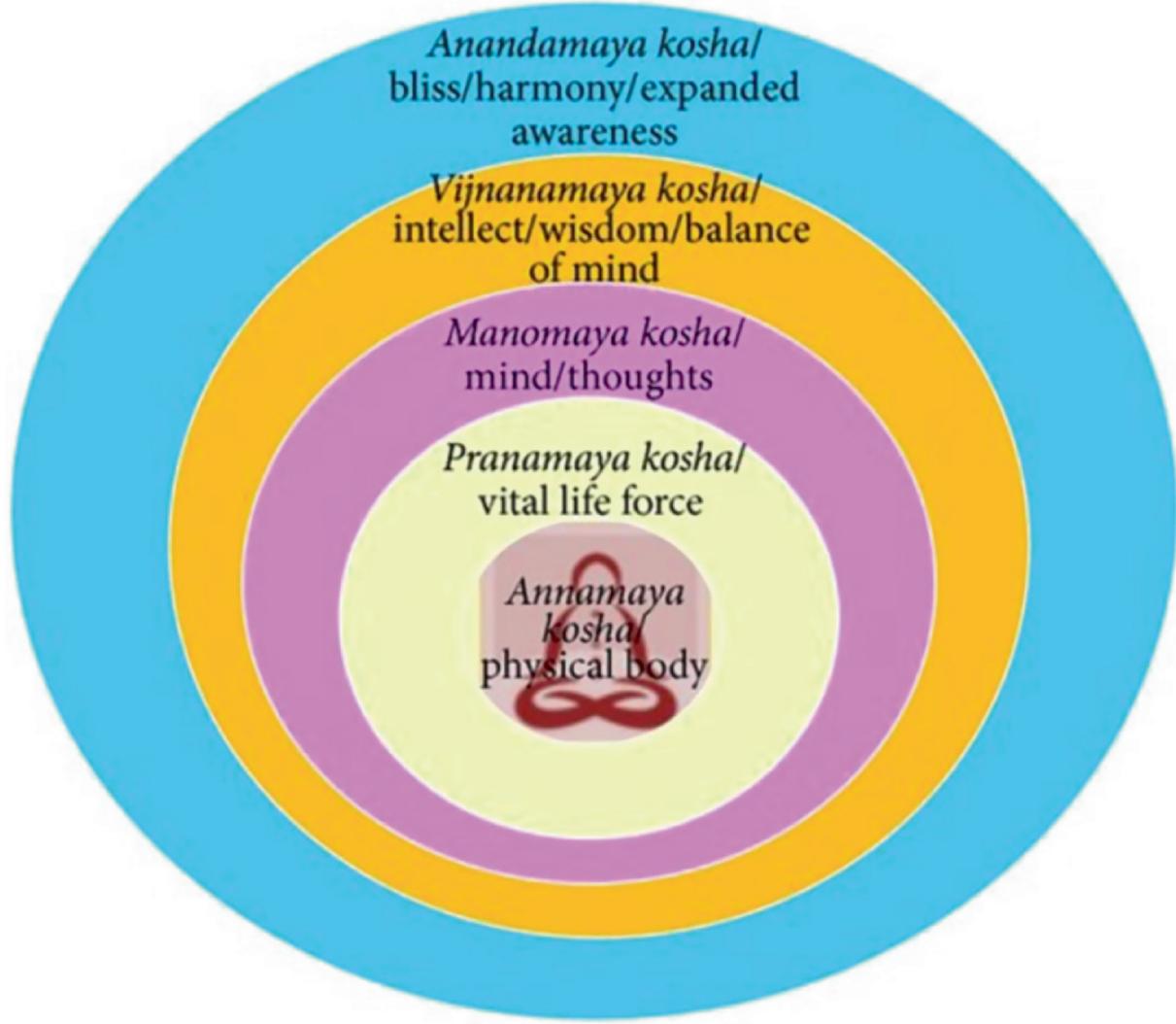


Fig. 6 Representation of Panch koshas-five elements of human existence.

Source [51]

Table 2 Summarising relationship between kosha theory and western theory of emotions

Kosha	Layer description	Role in emotions	Connection to western emotional theory	Example	Regulation strategies
Annamaya kosha (physical body)	Gross physical body made of food	Physiological expression of emotions (heart rate, muscle tension, sweating)	James-Lange theory—emotions begin with bodily changes	Sweaty palms and fast heartbeat before an exam	Physical exercise, progressive muscle relaxation, grounding techniques

Kosha	Layer description	Role in emotions	Connection to western emotional theory	Example	Regulation strategies
Pranamaya kosha (energy/breath body)	Breath and life-force energy regulating movement	Breath rate and energy flow shift with emotions	Autonomic nervous system response affects emotions	Short, shallow breaths during fear	Deep breathing, pranayama, paced breathing
Manomaya kosha (mental/emotional body)	Mind, sensory processing, and basic emotional patterns	Cognitive interpretation shapes emotional experience	Schachter-Singer theory —arousal + interpretation = emotion	Hearing loud noise, thinking it's danger → fear	Cognitive reframing, mindfulness, journaling
Vijnanamaya kosha (wisdom body)	Higher intellect, discernment, ego regulation	Evaluates and modulates emotional responses	Constructed emotion theory—prior concepts shape emotions	Realizing anger is due to misunderstanding	Self-reflection, meditation, therapy
Anandamaya kosha (bliss body)	Innermost layer of joy and peace	Stable joy beyond reactive emotions	Broaden-and-Build Theory —positive emotions expand resilience	Feeling deep contentment during meditation	Gratitude practice, compassion meditation, service

Source Summarised and compiled by authors (2025)

6.3 Indian Yogic Perspective on Emotions

In Indian school of thought, relationship between Yoga and Emotions can be seen in ancient philosophical texts like Yoga sutras of Patanjali and the Bhagvad Gita. Emotions are not viewed as independent psychological phenomena, but rather viewed as modifications of desire and attachment. Emotions arise from connection of ahamkara or ego with external world. The main cause of suffering or duhkha is considered owing to ignorance of the true self-atman. Controlling one's emotions is a vital first step on the path to self-realization [101]. The trigunas-sattva, rajas, and tamas which underlie emotional experiences determine its nature and intensity. Undesirable emotion can be transformed using breathwork and meditative

techniques leading to mental well-being and spiritual growth. Yoga sutras emphasize mindfulness, breathing exercises, meditation, and self-regulation techniques for emotional well-being, combining ancient wisdom with modern psychological insights to understand and master emotions [101].

6.4 Emotions as Viewed by Nyaya-Vaisesika, Vedanta, Samkhya, and Ayurveda

Classical Indian philosophical perspective does not have direct equivalent of western concept of “emotion”. They analyse phenomenon like rāga (attraction), dveṣa (aversion), śoka (sorrow), and bhaya (fear) through the lens of epistemology, metaphysics, and soteriology. They view emotion’s role in spiritual liberation and its interplay with cognition. They offer diverse yet complementary insights into emotions:

- Nyaya-Vaisesika school views emotions as mental states linked to desires and aversions, analyzed through logic and epistemology [99]. From the classical viewpoint, emotions like attraction and aversion are viewed as mental defects or *dosas* that arise from ignorance or *mithyagan*. This leads to attachment, misperception, obstructing path to right knowledge and thus hindering liberation. Pleasure and pain both are seen as obstacles to attaining nirvana or moksha. Contemporary academicians reaffirm this classical Nyaya-Vaisesika viewpoint and emphasize that *pramana* or right knowledge transcends emotional disturbances [89].
- Vedanta views mind as the seat of Emotions. Emotions are qualities of manas or mind and not of true self or *atman*. Detachment and knowledge can end emotional suffering and help individual to be in true state of self or ultimate reality i.e. *Brahman* [15]. Attributes of mental states like memory, imagination, fear, love, aversion etc. are seen as emotions belonging to manas or mind but not of atman i.e. eternal self. To achieve liberation, one must discriminate the self or atman from these transient mental functions or emotions, paving way towards Brahman [89].
- Samkhya philosophy views reality or world composed of two independent principles viz., *Purusa* and *Prakriti*. Purusa is consciousness or spirit, and prakriti is nature or matter. Emotions and mental states arise from this prakriti [89]. Samkhya philosophy categorizes emotions as resulting from interplay of the *trigunas* i.e. *sattva* (purity, harmony, clarity), *rajas* (activity, passion, restlessness), and *tamas* (inertia,

ignorance, dullness). These gunas affect emotional quality and mental states [102]. It is believed that higher sattva dominance will foster calmness, while dominance of rajas and tamas may stir agitation, or anxious overthinking or lethargy. Cultivating sattva via meditation will help bring emotional balance or serenity.

- Ayurveda integrates emotions into the framework of *doshas* (Vata, Pitta, Kapha) linking emotional disturbances to physiological imbalances and advocating lifestyle and herbal interventions to restore harmony [58]. Imbalances in *doshas* when interact with *trigunas* (Sattva, rajas, tamas) affect emotional and physical health. Steer [117] in study found that vata imbalance leads to more anxiety, rumination, less mindfulness, similarly, pitta imbalance can cause poor mood regulation, and stress; kapha imbalance also causes more stress along with rumination and less reflection [117].

These schools of thought together highlight a holistic and integrative understanding of emotions incorporating body, mind, and spirit. They offer therapeutic and philosophical pathways for emotional health (Table 3).

Table 3 Summarising understanding of emotions in Indian Philosophical School

School	Classical view	Modern insight	Example
Nyaya-Vaisesika	Emotions are defects that can impede cognition	Emotional states cloud perceptions; liberation can be achieved by eliminating them	Attachment to pleasure distorts truth
Vedanta	Emotions belong to mind (<i>Manas</i>), not the self (<i>Atman</i>)	True self transcends emotions	“I am not my anger”- leading to detachment
Samkhya	Emotions arise from interplay of <i>trigunas-Sattva, Rajas, Tamas</i>	Sattva fosters balance, equanimity, rajas and tamas disturb peace	Overactive mind (rajas) can be soothed via Sattva practices
Ayurveda	Emotional disturbances arise owing to <i>dosha</i> imbalances and <i>dosha-guna</i> interaction	Dosha-guna profiles correlate with anxiety, depression, and mood	Vata-rajas leads to anxiety, kapha-tamas lead to depression

Source Summarised and compiled by authors (2025)

6.5 Contrasts and Complementarities with Western Models

Emotions are viewed as discrete biological or cognitive events through Western psychological lenses, but Indian perspectives views emotion in a deeper integrative and experiential framework. Indian models combine

spiritual, cultural factors, and mind–body unity. Here emotions are viewed as fluid, dynamic, in the frame of context, and interconnected to broader existential concerns. Both traditions do recognize the importance of cognitive appraisal and bodily states in emotional experience.

The Indian viewpoint on emotional regulation by meditation and self-awareness is similar to Western approaches in clinical psychology which focus on mindfulness and cognitive-behavioral therapies [49]. However, Rasa Theory's emphasis on aesthetic aspect of emotions enriches the perception of emotional complexity and transcendent experiences. These are often underexplored in Western frameworks.

By integrating both Indian and Western perspectives, authors advocate for a culturally inclusive and multidisciplinary approach to research of emotion which respects both empirical rigor and philosophical depth.

7 Applications and Implications

7.1 Emotions in Forensic Psychology

Within the domain of forensic psychology, emotion play a crucial role. Theoretical frameworks of emotions are applied to assess, understand, evaluate and predict human behaviours related to legal investigations. Emotions or emotional arousal is utilised as scientific tool to assess truthfulness, or deception or emotional states of people involved in legal justice system. Tools like polygraph measure physiological stated like heartbeat, blood pressure and galvanic skin response (GSR) which help detect deception associated emotional arousal. The Facial Action Coding System (FACS) developed by Paul Ekman and Wallace V Friesen breaks down facial expression associated with various emotions via specific muscle movements. This can help detect deception along with concealed emotions [28]. Rationale behind Polygraph tests is rooted in the notion that deceptive behavior will trigger distinct emotional and physiological responses. Techniques like voice stress analysis (VSA), and layered voice analysis (LVA) analyses speech patterns linked to changes in vocal frequencies which can detect stress levels, cognitive states, emotional states and hence deception [42]. Recognising emotions is essential for social interaction, yet individuals with sexual offenses often show socio-affective deficits. In a study, Tiberi et al. [119] found that forensic inpatients (sexual and non-sexual offenders) displayed poorer emotion recognition and slower

responses than community members, with sexual offenders being especially cautious in labelling “surprise” [119]. These tools contribute to forensic investigations by providing objective and scientific measures of emotional responses. Their reliability and ethical implications remain subjects of ongoing debate. They are on case-to-case basis admissible in court of law as corroborative evidences based on expert testimony.

7.2 Role of Emotional Intelligence in Mental Health and Social Behavior

Emotional intelligence (EI) refers to the ability to perceive, appraise, understand, regulate, and utilize emotions. EI has emerged as a significant factor influencing mental health, interpersonal relationships, and social functioning [105]. High EI is linked with better stress management, resilience building, and adaptive coping strategies. These skills protect one against anxiety, depression, and emotional dysregulation [111]. Emotional intelligence enhances empathy and social skills, this results in healthier social interactions and efficient conflict resolution [10]. Emotion’s role in occupational setting and educational domain emphasises the importance of integrating emotional intelligence development in social skills training as well as mental health therapeutic interventions [71].

7.3 Clinical and Therapeutic Implications

Numerous clinical and therapeutic techniques aimed at improving mental health and regulating emotions are based on understanding that emotions are multifaceted and complex. By addressing maladaptive emotional evaluations and behaviours, cognitive-behavioral therapy (CBT) encourages more constructive emotional processing [7]. With their roots in Buddhist and yogic traditions, mindfulness-based therapies have demonstrated effectiveness in treating mood and anxiety disorders by emphasising nonjudgmental awareness of emotional states [49]. Pharmacology based treatments that alter emotional circuits linked to conditions like PTSD and depression have been made easier by affective neuroscience [22, 23]. These interventions show how important emotional intelligence is to creating successful mental health care plans.

7.4 Emerging Technologies: AI and Machine Learning in Emotion Recognition and Research

Emotion research has transformed with advent and progress of technology like artificial intelligence (AI) and machine learning (ML). AI & ML has enabled automated detection and analysis of emotional expressions using diverse data sources like facial images, speech patterns, texts, and other physiological signals [127]. Systems for emotion recognition use algorithms which is trained on large datasets and they do same with accuracy, which facilitates application in forensic setting, monitoring mental health, customer service and also human–computer interaction [13]. AI-driven tools and systems also support real-time emotion tracking in both virtual environments, and on social media. This opens up new avenues of application in behavioural research and therapeutic intervention [94, 97]. At the same time, ethical concerns regarding privacy, biases etc. in emotional data processing necessitates need for responsible development and regulation [19].

8 Future Directions and Emerging Trends

8.1 Advances in Neuroscience and Psychology Integration

The integration of neuroscience and psychology continues to deepen our understanding of emotions by revealing the neural substrates and mechanisms underlying emotional experiences. Cutting-edge neuroimaging techniques, such as functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG), enable researchers to map brain activity during emotional processing with increasing precision [92]. These advances support the development of more nuanced models that capture the dynamic interplay between cognition, physiology, and affect. Future research aims to unravel how brain plasticity influences emotional development and regulation, potentially informing novel interventions for emotional disorders [23].

8.2 Cross-Cultural and Interdisciplinary Research Prospects

Growing recognition of cultural variability in emotional experience and expression underscores the importance of cross-cultural research in emotion science. Interdisciplinary collaborations between psychology, anthropology, neuroscience, and philosophy are essential to developing culturally sensitive theories and assessment tools [75]. Such approaches facilitate understanding of how social norms, language, and cultural practices shape

emotions, expanding beyond Western-centric models. Interdisciplinary work also enriches applications in global mental health, education, and technology design, fostering inclusive frameworks that respect diverse emotional realities [122].

8.3 Potential for AI and Machine Learning to Decode Emotions

Artificial intelligence and machine learning hold transformative potential in decoding and interpreting complex emotional signals. By leveraging large multimodal datasets—combining facial expressions, vocal tone, physiological measures, and text—AI systems can detect subtle emotional cues with growing accuracy [127]. Advances in deep learning algorithms promise to enhance emotion recognition in real-world, dynamic environments, enabling personalized feedback and adaptive interventions [97]. However, ethical considerations, including data privacy, bias mitigation, and transparency, remain critical to responsible AI deployment in emotion research [19]. Future developments may integrate AI-driven emotion decoding with wearable technologies for continuous mental health monitoring and support [94].

8.4 Ethical Considerations in AI and Emotion Recognition

The use of artificial intelligence (AI) in emotion recognition also raises important ethical concerns, particularly regarding privacy and bias. Emotion recognition systems often rely on facial expressions, voice, or physiological signals to infer affective states. This creates risks of intrusive surveillance, especially when individuals are unaware that their emotions are being monitored or analyzed [74]. Such practices can undermine autonomy and violate rights to privacy, particularly in sensitive contexts such as workplaces, schools, or legal settings.

Another critical issue is algorithmic bias. AI models are often trained on limited or culturally skewed datasets, leading to systematic inaccuracies in recognizing emotions across different demographic groups. For instance, emotion recognition systems have been shown to misclassify expressions in women and people of color more frequently, which can perpetuate social inequalities [4]. Misinterpretations in forensic or clinical settings could have especially harmful consequences, such as reinforcing stereotypes or leading to unjust decisions.

Thus, while AI-based emotion recognition holds promise, its ethical use requires transparent data practices, diverse training datasets, and strict regulation to ensure fairness, accountability, and respect for individual rights.

8.5 Personalized Emotion Research: Implications for Mental Health

Personalized approaches to emotion research emphasize individual differences in emotional processing shaped by genetics, environment, culture, and life experiences [40]. Advances in genomics and neuroimaging facilitate identification of biomarkers linked to emotional disorders, enabling tailored therapeutic strategies [34]. Integration of personalized data with AI-assisted emotion recognition can support precision psychiatry, offering customized interventions based on an individual's unique emotional profile [44]. This paradigm shift promises to enhance prevention, diagnosis, and treatment of mental health conditions, promoting emotional resilience and well-being on a personalized scale.

9 Conclusion

This review has explored a wide spectrum of psychological theories on emotions, ranging from evolutionary and physiological models to cognitive, constructivist, and socio-cultural frameworks. Each theory contributes unique insights into the complex nature of emotions—highlighting their biological roots, cognitive appraisals, cultural shaping, and dynamic construction. The integration of these perspectives reveals that emotions are multifaceted phenomena involving intertwined physiological, psychological, and social processes.

Importantly, incorporating multidisciplinary and culturally inclusive approaches enriches our understanding by bridging Western scientific models with profound Indian philosophical traditions and emerging technological innovations. Such a comprehensive view acknowledges the universality of some emotional processes while respecting cultural variability and individual differences.

As emotion science continues to evolve, advances in neuroscience, artificial intelligence, and cross-cultural research promise to deepen our comprehension and application of emotional knowledge. Future research

must embrace this complexity, balancing empirical rigor with cultural sensitivity to better address mental health, social functioning, and human well-being globally.

Ultimately, emotions remain a fundamental yet evolving frontier in psychology—one that continues to challenge and expand our understanding of what it means to be human.

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Classical Face Recognition: Geometric Models, Subspace Techniques and Local Descriptors

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Abstract

Facial recognition research originated from the fundamental task of distinguishing individuals based on their facial characteristics. Early researchers did exactly that by measuring distances between eyes, noses and mouths, but these geometric tricks fell apart as soon as a smile, tilt or shadow got in the way. So they began looking at the whole face, compressing images into “eigenfaces” that captured the most common patterns. These principal components were fast and easy but not very discerning, prompting the search for discriminative features with Fisherfaces and even higher-order patterns with Independent Component Analysis. Others zoomed in on tiny patches, counting local binary patterns or filtering textures with Gabor wavelets to withstand changes in lighting and expression. This chapter traces that journey from hand-measured landmarks to clever mathematical subspaces and texture codes. It also touches on iconic datasets like Labeled Faces in the Wild, explains what it means for a system to falsely accept or reject someone, and reflects on why these “classical” techniques still matter. Even though deep neural networks now steal the spotlight, the simplicity and transparency of these older methods keep them useful for teaching, benchmarking and environments with little data or limited hardware.

Keywords Face recognition – Classical approaches – Geometric methods – Principal component analysis (PCA)/eigenfaces – Linear discriminant analysis

1 Introduction and Historical Perspective

The human brain performs face recognition effortlessly. We effortlessly pick out familiar faces in a crowd, notice subtle expressions and differentiate between twins, even under poor lighting. Reproducing this remarkable ability in a machine has been a major focus of computer vision research for over half a century. Long before the advent of deep learning, researchers built systems that sought to model how people recognise faces using carefully designed features and statistical models. These classical face recognition approaches emerged in a period stretching from the early 1970s to the early 2010s, and they laid the foundation for the powerful deep neural networks that dominate the field today.

Early face recognition research was heavily influenced by the capabilities and limitations of the computing hardware of the time. In 1964, Woodrow Bledsoe and collaborators at Panoramic Research Laboratories built one of the first semi-automatic face recognition systems. Their system required an operator to manually extract coordinates of key facial landmarks (such as the pupils, corners of the mouth and the width of the head). The program then used these measurements to compare the input image to a database of mugshots. Although far from automated, the approach demonstrated that faces could be described by geometric distances, and it set a precedent for geometric methods. In the 1970s and 1980s, researchers continued to refine landmark-based approaches, building statistical models of facial proportions and using techniques like the Karhunen–Loève transform to reduce dimensionality. These early efforts highlighted three enduring challenges: variations in lighting, facial expression and pose.

The 1980s saw a shift toward statistical pattern recognition. Sirovich and Kirby showed that a set of face images could be represented by a small number of orthogonal basis vectors derived from the covariance matrix of face images. These basis vectors came to be known as eigenfaces after Turk and Pentland applied them for classification [1]. Instead of measuring distances between specific landmarks, their system projected images into a lower-dimensional subspace spanned by the top eigenvectors of the covariance matrix. This work demonstrated that faces, though high-dimensional objects, reside on a low-dimensional manifold and can be discriminated using a compact representation.

Throughout the 1990s and early 2000s, researchers developed a variety of subspace and local feature methods to improve performance under variations in illumination, pose and expression. Linear Discriminant Analysis (LDA), also known as the Fisherface method, sought to maximise separability between

different people while minimising differences within the same person [2]. Independent Component Analysis (ICA) extended the idea of eigenfaces by capturing higher-order statistics, resulting in basis images that correspond to localized facial parts and outperforming PCA in some experiments [3]. Local Binary Patterns (LBP) and Gabor filters extracted texture information from small patches of the face, enabling more robust recognition under varying lighting and expression [4, 5]. The widespread availability of cameras and the growth of the internet led to the creation of large face datasets, such as FERET, Yale, ORL and Labeled Faces in the Wild (LFW) [6], which allowed researchers to systematically evaluate algorithms (Fig. 1).

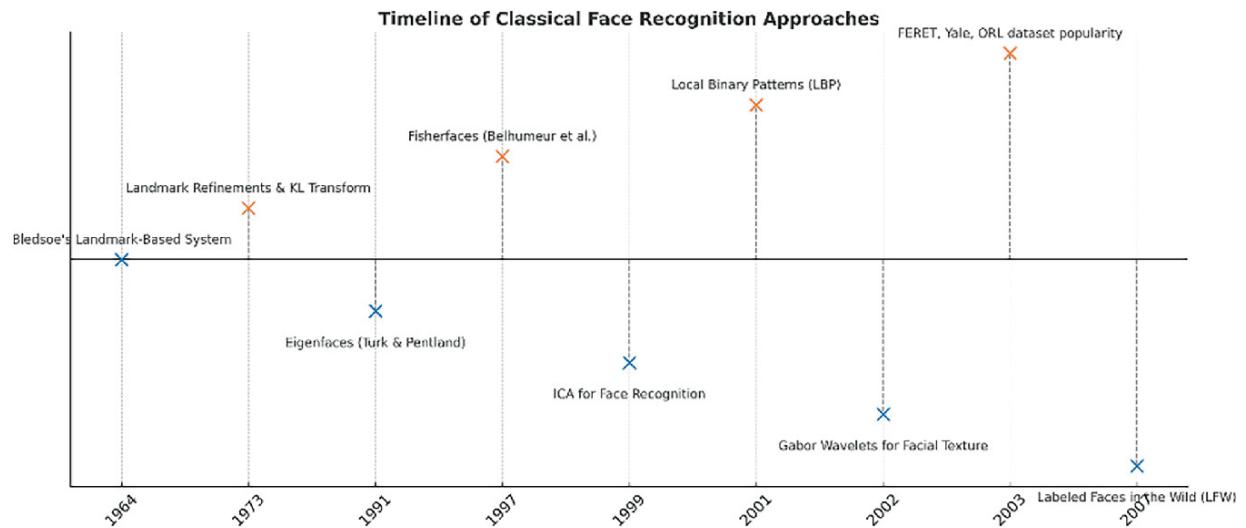


Fig. 1 Timeline of classical face recognition approaches

This chapter provides a comprehensive overview of classical face recognition approaches. Section 2 explores geometric and holistic subspace methods, detailing algorithms for Principal Component Analysis (PCA), Linear Discriminant Analysis, Independent Component Analysis and related techniques. Section 3 focuses on local feature-based methods, including Local Binary Patterns, Gabor features, Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT). Section 4 discusses public datasets and evaluation metrics such as False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (EER) [7]. Section 5 analyses the strengths and limitations of classical methods, and Sect. 6 summarises the state of the field and reflects on the relevance of these techniques in the era of deep learning.

2 Geometric and Holistic Subspace Methods

Classical face recognition methods fall into two main paradigms: geometric approaches that represent faces through measurements of facial landmarks, and holistic approaches that treat the entire face image as a vector and project it into a lower-dimensional subspace. Holistic methods often require less manual intervention than geometric ones and have generally performed better in unconstrained environments.

2.1 Geometric Face Recognition

The earliest endeavors in automated facial recognition drew inspiration from how humans intuitively recognize familiar individuals—often by noting the spatial arrangement and proportions of facial features. In the 1960s, researchers like Woody Bledsoe and colleagues attempted to formalize this process using geometric measurements derived from frontal facial images. Distances between key anatomical landmarks—such as the eyes, nose, mouth, and jawline—were manually recorded and structured into feature vectors.

One of the pioneering systems, described in Bledsoe's 1964 work, utilized Euclidean and Mahalanobis distance metrics to compare these vectors against stored templates. Despite being a breakthrough for its time, the system's performance was modest. Several core limitations hindered its scalability:

- Limitations of Geometric Models: Despite being a breakthrough for its time, early geometric face recognition systems suffered from several critical limitations that ultimately hindered their scalability and accuracy, especially in uncontrolled environments.
- Pose Sensitivity: Even slight head tilts or rotations (e.g., turning $\pm 15^\circ$ from a frontal view) significantly distort the perceived distances and angles between facial landmarks (eyes, nose, mouth). Since geometric models relied on 2D measurements, they lacked mechanisms to compensate for 3D head movement. This made them unreliable in surveillance scenarios where individuals rarely face the camera directly.
- Occlusion Vulnerability: Facial features can be partially or fully obscured by external elements such as glasses, hats, beards, or scarves. For example, the presence of thick-rimmed glasses could hide the eye corners, or facial hair could obstruct the mouth and chin regions. Because geometric models used a small set of predefined landmarks, any occlusion often led to incorrect or missing features, reducing recognition accuracy.
- Illumination Dependence: Geometric extraction methods—especially those based on edge detection or gradient information—are highly sensitive to lighting variations. Shadows cast across the face, backlighting, or uneven illumination distort the visibility and accuracy of feature detection. These

limitations were especially evident when testing systems across different lighting setups (e.g., indoor vs. outdoor).

- Manual Annotation Burden: Early systems (such as Bledsoe's) required human operators to manually annotate the coordinates of each facial feature. This process was time-consuming, prone to human error, and non-scalable for large databases. Although semi-automated approaches emerged in the 1980s, reliable automatic landmark detection was not available until much later.
- Intra-Class Variability and Feature Ambiguity: Geometric models struggled to distinguish between individuals with similar facial proportions. For instance, two people might have nearly identical interocular distances and jaw widths, especially among family members or twins. Moreover, intra-class variability due to expressions (smiling vs. neutral) altered landmark positions and introduced noise in recognition.

Recognizing these constraints, the field advanced toward statistical shape modeling. Techniques like the Active Shape Model (ASM) and its successor, the Active Appearance Model (AAM), represented a major leap forward in the 1990s. Rather than relying solely on distances, ASM applied Principal Component Analysis (PCA) to landmark coordinates gathered from annotated training images. The result was a deformable shape model capable of adapting to new faces by varying along statistically learned modes.

AAM further extended this approach by simultaneously modeling both shape and texture. It aligned face images to a mean shape and then applied PCA to the texture (i.e., pixel intensities) within the warped region. These models enabled more robust face alignment and tracking, yet remained sensitive to initialization errors and partial occlusions. For example, poor starting positions often led to convergence on incorrect facial configurations.

Another significant contribution in this era was the Elastic Bunch Graph Matching (EBGM) technique, which introduced a structured and flexible representation of the face. EBGM constructed a graph of nodes anchored at salient landmarks (e.g., eye corners, nose tip, mouth edges). Each node stored a “jet”—a set of Gabor filter responses computed at multiple scales and orientations—encapsulating both the topological layout and local texture. During recognition, the algorithm searched for optimal correspondences between the input face graph and those in the database, allowing for elastic deformation to account for small changes in expression or pose.

Despite their historical impact, purely geometric models gradually declined in popularity due to the increasing demand for robustness in real-world applications. Their dependence on accurate landmark localization, particularly in low-resolution or unconstrained imagery, limited their standalone effectiveness.

Nevertheless, geometric cues remain relevant today, often serving as pre-processing steps for alignment or feature extraction in modern hybrid systems.

2.2 Principal Component Analysis and Eigenfaces

The Principal Component Analysis (PCA) technique revolutionised face recognition by shifting the focus from measuring geometric distances to analysing the entire face region. PCA is an unsupervised dimension reduction technique that finds orthogonal directions (principal components) along which the data vary the most. Given a set of centred training images (each reshaped into a vector), one forms a covariance matrix and solves the eigenvalue problem. The eigenvectors corresponding to the largest eigenvalues capture the directions of greatest variance, and they form a basis for the eigenface subspace [1].

In practice, a face image with $\mathbf{M} \times \mathbf{N}$ pixels is converted into a vector of length \mathbf{MN} . Stacking all \mathbf{p} training images into a matrix $\mathbf{X} \in \mathbf{R}^{(MN) \times p}$, one computes the mean face \mathbf{x} and subtracts it from each column: $\tilde{\mathbf{X}} = \mathbf{X} - \mathbf{x}\mathbf{1}^T$. The covariance matrix is:

$$\mathbf{C} = \frac{1}{\mathbf{p}} \tilde{\mathbf{X}} \tilde{\mathbf{X}}^T \quad (1)$$

Solving the eigenvalue problem $\mathbf{Cv}_i = \lambda_i \mathbf{v}_i$ yields the eigenfaces \mathbf{v}_i . Since \mathbf{C} is high-dimensional, Turk and Pentland proposed computing eigenvectors of the smaller matrix $\tilde{\mathbf{X}}^T \tilde{\mathbf{X}}$ and projecting them back to the original space using $\mathbf{u}_i = \tilde{\mathbf{X}} \mathbf{v}_i$. Once the top \mathbf{k} eigenfaces are obtained, a face image \mathbf{x} is projected into the subspace to obtain coefficients $\mathbf{y} \in \mathbf{R}^k$ using

$$\mathbf{y} = \mathbf{U}^T (\mathbf{x} - \mathbf{x}) \quad (2)$$

where \mathbf{U} contains the eigenfaces.

Classification can be performed by nearest neighbour search in this reduced space or by measuring reconstruction errors. In a verification setting, one computes the distance between the coefficients of two images and compares it to a threshold.

PCA-based methods were widely adopted because they require relatively few samples to learn a compact representation and are computationally efficient [8]. Eigenfaces capture global appearance variations such as illumination changes and coarse facial structure. However, because PCA does not consider class labels, it emphasises features with large variance rather than those that discriminate between individuals. Consequently, eigenfaces often include variations due to

lighting, pose and background, which may not be informative for identity. Research showed that eigenfaces perform poorly under occlusions and non-frontal poses [9]. To address this, researchers developed methods to add robustness, such as using multiple illumination subspaces or performing PCA on local patches.

2.3 Linear Discriminant Analysis (Fisherfaces)

LDA, also Known as Fisher's linear discriminant, is a supervised dimension reduction technique. Unlike PCA, which maximises overall variance, LDA seeks directions that maximise between-class scatter while minimising within-class scatter. For face recognition, LDA is applied to find a projection that best separates the classes (people) represented in the training set. The resulting basis vectors are sometimes called Fisherfaces [2].

Let the training set contain images from c different people (classes) with n_i images for person i . The within-class scatter matrix is defined as

$$S_W = \sum_{i=1}^c \sum_{x \in \text{class } i} (x - \mu_i)(x - \mu_i)^T, \quad (3)$$

where μ is the mean of class i . The between-class scatter matrix is

$$S_B = \sum_{i=1}^c n_i (\mu_i - \mu)(\mu_i - \mu)^T, \quad (4)$$

where μ is the overall mean. LDA finds a projection matrix \mathbf{W} that maximises the ratio of the determinants of the scatter matrices:

$$\mathbf{W} = \operatorname{argmax} \frac{\mathbf{W}^T S_B \mathbf{W}}{|\mathbf{W}^T S_W \mathbf{W}|}. \quad (5)$$

The solution involves solving the generalized eigenvalue problem $S_B u = \lambda S_W u$. The number of meaningful discriminant vectors is at most $c - 1$. In practice, S_W is often singular because the dimensionality of images is much larger than the number of samples; to mitigate this, Fisherfaces combine PCA and LDA by projecting the images into a subspace of moderate dimension using PCA, then applying LDA.

LDA typically provides better discrimination than PCA when multiple samples per person are available and the training set captures various expressions and lighting conditions. However, if the number of training images is small or the

number of classes is large, LDA may overfit the data. Furthermore, because LDA learns a linear discriminant, it may not capture complex nonlinear variations. Nonlinear variants such as Kernel Fisher Discriminant Analysis map the data into a high-dimensional space using kernels before performing LDA, enabling better separation.

2.4 Independent Component Analysis

Independent Component Analysis (ICA) extends PCA by finding components that are statistically independent rather than merely uncorrelated. While PCA looks for orthogonal directions that capture maximum variance, ICA aims to recover latent variables whose linear combinations produce the observed data. Applying ICA to faces often yields basis images that resemble localized facial features such as eyes, mouths and noses, which can capture high-order statistics.

One formulation of ICA assumes that the observed data X (zero-mean) is generated by mixing independent sources S using an unknown mixing matrix $A:X = AS$. The goal is to estimate an unmixing matrix W such that $S = WX$. ICA algorithms, such as FastICA, use measures of non-Gaussianity (e.g., kurtosis, negentropy) or maximum likelihood estimation to find W . Bartlett, Movellan and Sejnowski compared two architectures for ICA-based face recognition: architecture I, which represents each face as a combination of basis images (global features), and architecture II, which treats each basis image as a filter and represents faces by filter responses (local features). Both architectures outperformed eigenfaces on tests involving variations in expression and time [3].

ICA has several advantages over PCA and LDA. First, by exploiting higher-order statistics, it can capture independent features that are more discriminative and it should handle faces lit from different angles and faces showing different expressions without losing accuracy. Second, the locality of ICA basis images resembles the receptive fields of neurons in the visual cortex, suggesting a biological plausibility. However, ICA is computationally more expensive than PCA, and the independence assumption may not hold in practice. Moreover, ICA lacks a natural ranking of components by importance; therefore, selecting an appropriate number of components is less straightforward than in PCA (Fig. 2).

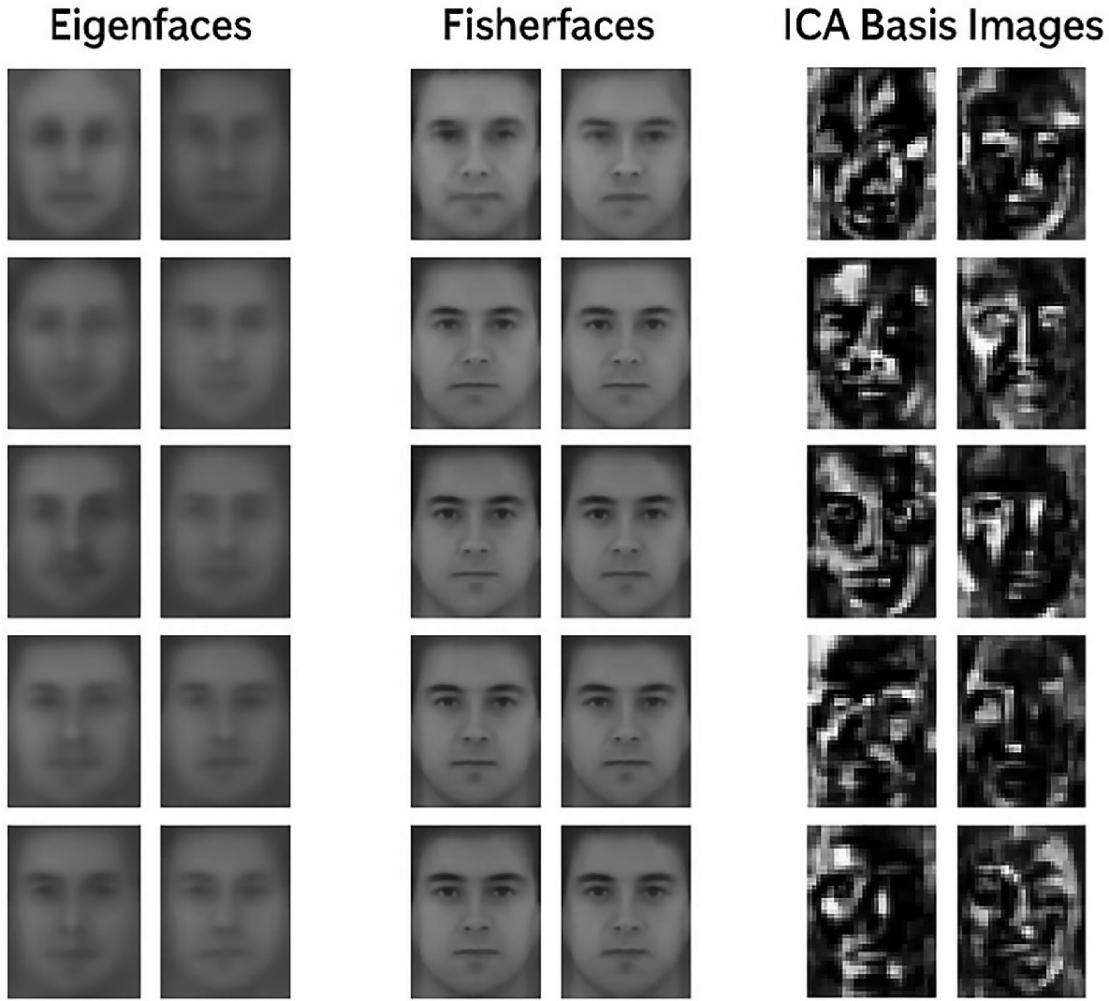


Fig. 2 Visual comparisons: eigenfaces versus fisherfaces versus ICA basis images

2.5 Other Subspace Methods

In addition to PCA, LDA and ICA, researchers developed various other subspace methods to improve face recognition performance under different conditions.

a. Kernel PCA and Nonlinear Methods

Kernel Principal Component Analysis (Kernel PCA) addresses the limitations of linear PCA by performing PCA in a high-dimensional feature space implicitly defined by a kernel function. Using kernels such as the Gaussian radial basis function or polynomial kernels, Kernel PCA can capture nonlinear variations in facial appearance. Similarly, Kernel LDA applies LDA in the kernel space to find nonlinear discriminant directions. These methods improve recognition performance when the variations between different images of the same person are

nonlinear, but they require choosing appropriate kernel parameters and can suffer from high computational cost.

b. Random Subspace Methods and Ensemble Learning

The Random Subspace Method (RSM) randomly selects subsets of features (e.g., pixels or eigenface coefficients) and trains multiple classifiers on these subsets. The final decision is obtained by combining the outputs of individual classifiers (e.g., via majority voting). RSM reduces the risk of overfitting and improves robustness by diversifying feature sets. Researchers applied RSM to eigenfaces and Fisherfaces, achieving improved recognition rates on the FERET and Yale datasets. Bagging and Boosting are other ensemble techniques that combine weak classifiers to form a strong classifier. AdaBoost has been used with Gabor features to select the most discriminative features for face recognition.

c. Local Subspace Analysis

While PCA computes a single global subspace for all images, Local Subspace Analysis builds multiple subspaces that capture different modes of variation such as pose, illumination or expression. Another family of techniques falls under manifold learning. The key idea is that even though a digital portrait is a very high-dimensional vector, the set of all possible faces lies on a much lower-dimensional, curved surface (a “manifold”) in that space. Methods such as Isomap, Locally Linear Embedding (LLE) and Laplacian Eigenmaps attempt to unfold that surface by examining how each face image relates to its closest neighbours. By preserving these local relationships, they reveal the underlying structure of facial variations like pose or expression. Once the manifold is learned, new faces can be embedded and compared via geodesic distances. These algorithms provide insights into the intrinsic dimensionality of face images but are sensitive to noise and require sufficient sampling.

2.6 Discussion

Holistic subspace methods transform high-dimensional image vectors into compact representations that capture the most informative variations. PCA-based eigenfaces established that faces can be represented using only a few hundred coefficients, enabling real-time recognition on modest hardware. LDA improved discriminability by focusing on between-class variance [2], and ICA captured independent localized features [3]. These methods were widely used because they are mathematically elegant and computationally efficient. However, they rely on

linear assumptions and often struggle with large pose variations and occlusions. They also require careful alignment of faces; misaligned eyes or mouths can lead to significant errors. To overcome these limitations, researchers turned to local feature-based approaches, which are the subject of the next section (Table 1).

Table 1 Comparative recognition performance of classical face recognition methods

Method	Approach type	Main feature	FERET accuracy (%)	ORL accuracy (%)	Yale accuracy (%)	Strengths	Limitations
PCA (eigenfaces)	Subspace	Maximizes variance across all samples	85–90	93–96	~83	Simple, low dimensionality	Sensitive to lighting and pose
LDA (fisherfaces)	Subspace	Maximizes class separability	88–94	96–98	~86	Good class discrimination	May overfit with few samples
ICA	Subspace	Captures independent sources, localized features	90–95	~97	~87	Robust to lighting and expression	Computationally heavier
LBP	Local descriptor	Texture-based local patterns	92–96	~98	2	Robust to lighting and occlusion	Sensitive to noise and misalignment
Gabor filters	Local descriptor	Multi-scale and multi-orientation filtering	94–97	~98	~91	Excellent robustness to illumination variation	High computational cost

3 Local Feature-Based Methods

Holistic methods summarise the entire face into a single vector, but this can make them sensitive to global variations in illumination, pose and expression. Local feature-based methods address this by extracting features from small neighbourhoods or keypoints. They focus on capturing fine texture details and structural information that remains stable across varying conditions. Some of the most influential local methods include Local Binary Patterns (LBP), Gabor filters, Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT) and their combinations.

3.1 Local Binary Patterns (LBP)

Local Binary Patterns were introduced as a texture descriptor and later adapted for face recognition [4]. Local descriptors such as Local Binary Patterns (LBP) and Gabor wavelets gained popularity due to their strong resilience to illumination variations and their computational efficiency. These methods extract local texture or frequency information, allowing for stable recognition under changes in lighting, pose, and expression. In contrast to holistic methods like PCA and ICA, which rely on global appearance, local descriptors can capture discriminative micro-patterns that remain consistent across sessions. The basic LBP operator works on a 3×3 pixel block. For each pixel, its value is compared to each of its eight neighbours. If the neighbour's value is greater than or equal to the center pixel, a value of 1 is assigned; otherwise, 0. Reading the binary values from the neighbours in a clockwise order forms an 8-bit binary pattern, which is converted to a decimal number between 0 and 255. This number indicates the local texture around the pixel. The LBP image for a face is built by computing the LBP code at each pixel, and a histogram of these codes summarizes the distribution of micro-patterns across the face. Since LBP codes are invariant to monotonic grayscale changes, they are robust to variations in illumination.

Several improvements to the basic LBP have been proposed. Uniform LBP counts the number of transitions (0–1 or 1–0) in the pattern and labels patterns with few transitions (e.g., 0–2) as uniform, assigning a single bin for all non-uniform patterns. This reduces the length of the histogram while preserving discriminative power. Circular LBP extends the neighbourhood to any radius, allowing for multi-scale texture analysis. Rotation-Invariant LBP rotates the binary pattern to the minimum possible value to handle rotated faces. Another powerful extension is Spatially Enhanced LBP, which divides the face image into an array of subregions (e.g., 7×7) and computes a histogram for each region. Concatenating these histograms forms a long feature vector that encodes both the local texture and its spatial location. This approach improves recognition accuracy because it preserves structural information [4].

To classify faces using LBP, one computes the LBP histograms of the training images and then measures the Chi-square distance or Histogram Intersection distance between the histograms of a test image and those of gallery images. The identity corresponding to the closest histogram is assigned. The simplicity and efficiency of LBP make it suitable for real-time applications, including face liveness detection and expression recognition. However, LBP is sensitive to image noise, particularly when neighbourhoods are small. It also struggles when faces are misaligned or subject to extreme pose changes. Combining LBP with robust alignment techniques or other descriptors can alleviate these issues.

3.2 Gabor Filters and Wavelet Transform

Gabor filters are linear filters that capture spatial frequency and orientation information. A two-dimensional Gabor filter is defined as a sinusoidal plane wave multiplied by a Gaussian envelope. Gabor filters mimic the receptive fields of simple cells in the human visual cortex. Applying a bank of Gabor filters at multiple scales and orientations to a face image yields a set of Gabor wavelet coefficients that represent local orientations and textures.

For face recognition, one typically uses a set of Gabor filters with 5 scales and 8 orientations, resulting in 40 filter responses per pixel. The responses around key facial points (such as eyes, nose and mouth) are concatenated to form a feature vector. Wiskott et al. used Gabor jets in their EBGM approach and showed that Gabor coefficients are more powerful than geometric distances for face recognition [5]. Another popular approach is the Gabor Fisher classifier, which applies PCA and LDA on the Gabor feature vectors to reduce dimensionality and perform classification. Gabor features are robust to variations in illumination and facial expressions and have been widely used in commercial face recognition systems.

Despite their effectiveness, Gabor filters produce very high-dimensional feature vectors, leading to significant computational and storage requirements. Dimensionality reduction techniques such as PCA, LDA and Generalized Discriminant Analysis (GDA) are often employed to manage this complexity. Additionally, because Gabor filters respond strongly to edges, they can be sensitive to noise and alignment errors. Preprocessing steps like histogram equalization and face alignment are commonly used before applying Gabor filters.

3.3 Histogram of Oriented Gradients (HOG)

The Histogram of Oriented Gradients (HOG) descriptor was originally developed for human detection but has been successfully applied to face recognition. HOG divides an image into small cells (e.g., 8×8) and computes a histogram of gradient orientations within each cell. The gradient magnitude is used as the weight for each orientation. Adjacent cells are grouped into blocks for contrast normalization, improving robustness to illumination changes. The concatenated histograms of all blocks form the HOG descriptor. HOG captures the general shape and structure of the face, such as the contour of the eyes, nose and mouth. While HOG does not capture as detailed texture information as LBP or Gabor features, it is robust to small deformations and lighting changes. Combining HOG with other descriptors or machine learning classifiers (e.g., Support Vector Machines) can yield high recognition accuracy.

3.4 Scale-Invariant Feature Transform (SIFT) and SURF

The Scale-Invariant Feature Transform (SIFT) is a keypoint-based descriptor that detects distinctive points in an image and describes them by gradient histograms. SIFT keypoints are invariant to rotation and scale and robust to small affine transformations. For face recognition, SIFT detects keypoints on salient facial regions (e.g., eyes, nose corners, mouth corners). For each keypoint, a 128-dimensional descriptor is computed by binning gradient orientations in a 4×4 neighbourhood. To compare two faces, one matches SIFT descriptors between the images using distance metrics and counts the number of matches.

Alternatively, one can build a Bag-of-Features (BoF) model that represents a face by the frequency of visual words obtained by clustering SIFT descriptors. SIFT is particularly useful for cross-domain recognition, where faces may vary significantly in scale and orientation.

Speeded Up Robust Features (SURF) is a faster alternative to SIFT. SURF uses integral images to compute responses and approximates Gaussian second-order derivatives with box filters. SURF descriptors are shorter (64 dimensions) and have faster matching. In face recognition, SURF performs similarly to SIFT but is less computationally intensive.

3.5 Hybrid and Learned Local Representations

Recognizing that different descriptors capture complementary information, researchers combined multiple local features. Local Gabor Binary Pattern (LGBP) concatenates LBP histograms computed on Gabor filter responses, exploiting both orientation selectivity and binary encoding. HOG–LBP and SIFT–LBP features similarly merge edge information and texture patterns. The combination of descriptors often improves robustness to variations in pose and illumination.

Another category of local methods involves learned descriptors. Before deep neural networks, researchers used unsupervised learning methods such as Sparse Coding and Local Non-Negative Matrix Factorization to learn dictionary elements from patches of face images. Each patch is represented by a sparse combination of dictionary atoms, and these sparse codes are pooled and concatenated to form the face descriptor. While not purely handcrafted, these methods still fall under classical approaches because they do not involve end-to-end learning on millions of images.

3.6 Discussion

Local feature-based methods provide robustness against changes in lighting, expression and pose because they capture fine details that remain consistent across conditions. LBP is extremely simple and efficient [4], while Gabor filters mimic the response of human visual cortical cells and capture multi-scale,

multi-orientation information [5]. HOG and SIFT were originally developed for general object recognition but found application in faces due to their invariance properties. Hybrid descriptors combine the strengths of individual methods at the cost of longer feature vectors and more complex matching. One disadvantage common to many local methods is their sensitivity to misalignment; accurate face detection and alignment (e.g., eye normalization) are essential. Furthermore, high-dimensional feature vectors require dimensionality reduction or efficient indexing for large galleries (Table 2).

Table 2 Comparative characteristics of local versus holistic face recognition methods

Method	Feature type	Illumination robustness	Computational cost	Discriminative power	Common use	Cases
LBP	Local binary patterns	High	Very low	Moderate	Real-time systems	Mobile devices
Gabor filters	Frequency-based local textures	High	Moderate	High	Expression-variant recognition	Facial analysis
Eigenfaces (PCA)	Global appearance	Low	Low	Low to moderate	Dimensionality reduction	Baseline comparison
Fisherfaces (LDA)	Global + class labels	Moderate	Moderate	Moderate to high	ID verification	Closed-set classification
ICA	Statistical independence of features	Moderate	High	High	Robust recognition	Under occlusion

4 Datasets and Evaluation Metrics

Benchmark datasets and standard metrics are critical for comparing face recognition algorithms. Because performance can vary widely depending on factors such as pose, illumination and occlusion, researchers use datasets with different characteristics and report multiple metrics.

4.1 Classic Datasets

- **Yale Face Database:** Picture a small group of 15 volunteers photographed in a studio under 11 different lighting setups and wearing a variety of expressions. Because everything else is controlled, this collection is ideal for showing how algorithms like PCA, LDA and LBP handle changes in illumination and mood [10].
- **ORL (AT&T) Face Database:** This classic set contains 400 portraits of 40 people, each photographed 10 times. Subjects sit upright against a plain dark

background, occasionally wearing glasses or smiling. Its modest size and consistency have made ORL a favourite for testing subspace methods and teaching students the basics [11].

- FERET: Commissioned by the U.S. Department of Defense in the 1990s, the FERET program amassed more than 14,000 images of 1,199 individuals. It introduced a formal gallery/probe testing protocol and includes frontal shots alongside variations in pose and expression. The sheer variety in FERET makes it a rigorous proving ground for classical algorithms [12].
- Extended Yale B: This dataset zeroes in on the challenges of lighting. Twenty-eight people were photographed under 64 different light sources and nine head poses, producing a catalogue of how shadows and highlights distort facial appearance. Researchers often use Extended Yale B to test algorithms that explicitly model illumination [13].
- CMU PIE: Short for Pose, Illumination and Expression, this collection features 68 subjects captured under 13 different poses, 43 lighting conditions and 4 facial expressions. By mixing pose and lighting changes, PIE exposes the weaknesses of methods that assume well-lit, frontal faces [14].
- Labeled Faces in the Wild (LFW) [6]: In contrast to the controlled sets above, LFW contains over 13,000 photos of nearly 6,000 people scraped from the internet. Faces are centred but appear in countless poses, lighting conditions and backgrounds. LFW popularized two tasks—verification (do these two photos show the same person?) and identification (who is this person?)—and quickly became the standard benchmark for face recognition “in the wild.”
- MegaFace, YouTube Faces and CASIA-WebFace: Introduced during the deep-learning era, these massive datasets contain millions of images and thousands of identities captured from online photos and videos. They illustrate how classical methods struggle to scale to very large galleries or to cope with the extreme variation found in real-world media [15].

4.2 Evaluation Metrics

Face-recognition technology can work in two fundamentally different modes. Verification is like checking a passport: the system compares a presented face against a single stored template to answer “is this the same person?”

Identification is more like searching through a crowd: the system scans a gallery of templates to find the best match. How we judge performance depends on which task we’re doing.

a. Verification Metrics

In verification, the system generates a similarity score for a pair of images and compares that score to a threshold to decide if they belong to the same person. We care about several types of errors:

- False Acceptance Rate (FAR): the percentage of impostor attempts that are incorrectly accepted as genuine. It is also called the False Match Rate (FMR). A low FAR is important when security is critical [7].
- False Rejection Rate (FRR): the percentage of genuine attempts that are wrongly rejected, also known as the False Non-Match Rate (FNMR). A low FRR ensures that authorized users aren't inconvenienced [7].
- Equal Error Rate (EER): the point on a DET or ROC curve where the FAR and FRR [16] are equal. It provides a single number summarizing the trade-off between the two types of errors; lower EER indicates a better-balanced system.
- Receiver Operating Characteristic (ROC) curve: a plot of the false rejection rate (1 minus the true positive rate) against the false acceptance rate across different thresholds. The area under the curve (AUC) is often used as an aggregate measure of performance—the closer to 1, the better [17].
- Detection Error Tradeoff (DET) curve: similar to the ROC curve but plotted on a logarithmic scale. It highlights differences in error rates when FAR and FRR vary across several orders of magnitude, making it useful for high-security applications [18].

b. Identification Metrics

In identification, the system searches a gallery of known identities for the best match. Metrics include:

- Rank-1 Accuracy: the proportion of probes whose top match is the correct identity. Higher rank-1 accuracy indicates better performance [19–21].
- Cumulative Match Characteristic (CMC) Curve: shows the probability that the correct identity is within the top k matches, for $k = 1, 2, \dots$. It provides insight into how quickly the recognition rate improves as more matches are considered [19–21].
- Identification Rate at Specified FAR: the probability of correct identification at a given false acceptance threshold. This metric is important for applications where security constraints limit the acceptable FAR [7].

Regardless of the metric, researchers often report results on multiple datasets to demonstrate the generalizability of their algorithms. Some metrics, such as FAR and FRR, depend on the chosen threshold; thus, presenting ROC or DET

curves allows readers to visualize the trade-off and select an appropriate operating point for their application.

4.3 Experimental Protocols

To ensure fair comparisons, datasets typically specify training and testing splits and provide pre-processed face images. For example, LFW defines View 1 for model selection and View 2 for testing; researchers report results using tenfold cross-validation. The Blended Face Recognition (BFR) evaluation protocol defines open-set identification tasks (where the probe may not appear in the gallery) and includes metrics like False Discovery Rate. Some protocols emphasize cross-pose or cross-illumination evaluation. When reporting results on classical methods, it is important to follow the prescribed protocol and clearly state pre-processing steps (e.g., histogram equalization, face alignment).

4.4 Biometric Evaluation Metrics

In biometric systems, evaluating recognition performance involves quantifying both the accuracy and the error trade-offs. Two fundamental error metrics are:

- False Acceptance Rate (FAR): The probability that an unauthorized (impostor) subject is incorrectly accepted by the system.
- False Rejection Rate (FRR): The probability that an authorized (genuine) subject is incorrectly rejected.

These two rates are typically evaluated across different threshold values to generate the Receiver Operating Characteristic (ROC) curve, which plots FAR against True Acceptance Rate ($TAR = 1 - FRR$). The ROC curve offers a comprehensive view of the system's trade-off between security and convenience.

Another key metric is the Equal Error Rate (EER), the point at which FAR and FRR are equal. A lower EER indicates better overall performance.

In verification scenarios (1:1 matching), ROC curves and EER are standard. In identification scenarios (1:N matching), metrics like Rank-1 accuracy and Cumulative Match Characteristic (CMC) curves are also used to assess the likelihood of the correct identity appearing in the top-k matches.

5 Strengths and Limitations of Classical Methods

Classical face recognition methods possess several strengths that made them popular for decades. They are interpretable; for example, eigenfaces can be visualized as images that highlight the most significant variations in the dataset. Subspace methods are computationally efficient, enabling real-time recognition on early hardware. Local descriptors like LBP and Gabor features are resilient to

moderate illumination changes and capture fine details that generalize across images [4, 5]. Because classical methods do not require massive amounts of training data, they are suitable for applications with limited labelled faces or for educational purposes.

However, these methods also have limitations. Linear assumptions restrict subspace methods such as PCA, LDA and ICA, making them less effective under large nonlinear variations in pose and illumination. Alignment sensitivity is a major issue; misaligned eyes or mouth positions degrade recognition accuracy. Global features like eigenfaces incorporate background information and lighting changes that may not be relevant to identity [9]. Local descriptors mitigate some of these problems but are still susceptible to noise, occlusion and extreme pose changes. Furthermore, classical methods struggle to scale to millions of identities because distance computations over large galleries become expensive and the features may not be sufficiently discriminative. These limitations paved the way for the transition to deep learning, which automatically learns hierarchical, nonlinear features from large datasets.

6 Conclusion and Outlook

This chapter has reviewed the historical evolution of classical face recognition methods, tracing their journey from early geometric techniques to powerful local descriptors. These approaches laid essential groundwork for today's deep learning-based systems, not only by offering insights into facial representation but also by inspiring many core principles of modern computer vision.

Looking forward, classical methods retain value in edge computing scenarios and hybrid architectures, offering computational efficiency and interpretability in environments where deep models may be impractical or opaque. By blending traditional and modern techniques, researchers can build more efficient, ethical, and adaptable face recognition solutions.

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Integrating Acoustic Feature Extraction and LSTM Models for Emotion Classification in Speech

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Abstract

Speech emotion recognition is a practice of integrating acoustic characteristic of a spoken speech so as to identify and label the emotional disposition of the speaker. In the present paper, an end-to-end architecture of the speech emotion recognition is going to be presented using the RAVDESS data set. This methodological integration includes natural features extraction, high quality of audio processing, smart data augmentation, and deep learning that enabled the successful categorization of emotional speech signals. In this paper, the descriptions of the arrangements performed on its RAVDESS dataset to arrange it by actor in actor-specific subdirectories and the cautious readiness of the audio files are presented as the basis of the paper. The key characteristics are obtained through the assistance of Librosa library; they are provided to be zero-crossing rate, root mean square energy, Mel spectrograms, and Mel-frequency cepstral coefficients (MFCCs). The results show that the

combination of the traditional signal processing approaches and the modern neural networks architecture, like Long Short Term Memory (LSTM) based models, contributes to the high accuracy speech emotion recognition.

Keywords Speech emotion recognition – Acoustic feature extraction – Spectrograms – Long short-term memory – Mel-frequency cepstral coefficients

1 Introduction

One of the fast-developing areas in affective computing is speech emotion recognition. It enables machines to comprehend human emotional states and express them based on voice [1]. This technology has the potential to improve interactions between humans and computers, customize virtual assistants, support mental health diagnostics, and adapt learning systems. Since humans rely heavily on emotional signals in ordinary communication, making machines able to recognize them will make machines more empathetic and contextual [2].

Recent advancements in machine and deep learning have transformed how emotion is identified. Past systems relied on manual features and rule-based methods. These are now being replaced with data-driven models that can uncover complex patterns in large datasets [3]. This paper offers a detailed description of speech emotion recognition using one of the most well-known databases—the RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song) [4]. The continued high-quality audio recordings of professional actors in RAVDESS, covering a wide range of emotions, make it a preferred choice for building stable speech emotion recognition systems.

Data preparation is the first step in the approach. The RAVDESS dataset is arranged in actor-specific directories to simplify preprocessing. Later, the Librosa library is used to extract acoustic features such as zero-crossing rate, root mean square energy, Mel spectrograms, and Mel-frequency cepstral coefficients (MFCCs). These features describe both the time-varying and spectral properties of speech, providing a snapshot of emotional cues. To account for inconsistencies in real-world audio, the framework applies data augmentation techniques such as noise injection, pitch shifting, time stretching, and signal shifting. These methods create

varied forms of the original recordings, simulating different acoustic conditions and introducing diversity to the training set. This helps the deep learning model generalize better to realistic sounds.

The extracted features are then fed into a deep neural network. The architecture combines convolutional layers, which capture local features, with a bidirectional LSTM, which models long-term temporal relationships. This hybrid model effectively captures the dynamics of speech signals and classifies audio inputs into eight emotion categories. It provides a deeper analysis of the speaker's emotional state. The framework can also leverage parallel processing during feature extraction to improve computational efficiency and scalability, making it more feasible for real-world applications.

In short, this study proposes a complete pipeline that combines advanced signal processing, robust data augmentation, and progressive deep learning methods for effective speech emotion recognition. Using the RAVDESS dataset and this methodology, the study contributes meaningfully to affective computing research and brings us closer to systems that can understand and respond to human emotions.

2 Literature Review

New breakthroughs in deep learning and signal processing have greatly advanced the area of speech emotion recognition. In early research, the focus was on hand-engineered features such as Mel-frequency cepstral coefficients (MFCCs), zero-crossing rates, and other spectral characteristics. These were extracted from speech signals and then classified using common methods such as support vector machines (SVMs) or Gaussian mixture models (GMMs) [5]. Although these approaches laid the foundation for emotion recognition, they failed to capture fine time-scale variations and the context-dependent nature of emotions.

The invention of deep learning changed this paradigm. Spectrograms combined with Convolutional Neural Networks (CNNs) have been successful in learning spatial hierarchies of features. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been effective in modeling temporal patterns in speech [6]. Hybrid CNN-Bidirectional LSTM architectures yield better results by capturing local spectral trends together with long-term temporal

connections [7]. This combination has led to significant improvements in emotion classification accuracy on datasets such as RAVDESS.

Despite these encouraging developments, several research gaps remain. One major limitation is the reliance on relatively small, controlled datasets. Many datasets lack diversity, as they are often created in artificial conditions. This restricts the robustness and generalization of models when applied to real-world scenarios, where factors such as background noise, accents, and recording conditions can heavily affect performance [8, 9].

Another issue lies in data augmentation. Most studies use simple techniques such as noise injection, pitch shifting, time stretching, and signal shifting. However, little research has explored systematic methods to combine and optimize these techniques [10]. Using them in isolation often limits the model's adaptability and can reduce performance in unforeseen scenarios [11]. Thus, current augmentation practices lack a holistic framework for enhancing data effectively.

Computational efficiency and scalability also remain central challenges. Traditional pipelines process audio files sequentially, which is time-consuming when handling large datasets. Although some studies have experimented with parallel processing, comprehensive application of such techniques in both feature extraction and model training is rare. This limits the feasibility of deploying emotion recognition systems in real-time applications [12, 13]. Another important but underexplored area is interpretability. Deep learning systems often act as black boxes [14]. They achieve high accuracy but provide little insight into how decisions are made. This lack of transparency is problematic in domains such as healthcare or service delivery, where the reasoning behind predictions is crucial [15].

Our proposed research addresses these gaps with an integrated approach. First, we adopt a systematic data augmentation strategy. Instead of using techniques individually, our framework combines noise injection, pitch shifting, time stretching, and signal shifting in a structured way. This creates more diverse and realistic training data, making the models more robust. Second, we employ parallel processing for feature extraction. By leveraging multi-core processors, our system minimizes computational overhead, scales efficiently to large datasets, and significantly reduces training and deployment time. This makes real-time execution more practical [16]. Third, our framework introduces a hybrid model composed

of convolutional layers and Bidirectional LSTMs. This design captures both complex frequency patterns and temporal information, allowing the model to learn robust representations of emotional speech. As a result, it achieves state-of-the-art performance on the RAVDESS dataset.

Finally, our framework improves interpretability. By combining systematic feature extraction with visualization techniques, we provide valuable insights into how the model reaches its decisions. This transparency is critical for building trust in automated speech emotion recognition systems, especially in sensitive applications. Overall, our approach not only enhances performance but also addresses key challenges of data diversity, computational efficiency, and model interpretability.

3 Proposed Methodology

It describes a holistic architecture of the speech emotion recognition in voice that would begin with data collection and preprocessing, be followed by extraction and augmentation of features, and conclude by the derivation, training, and testing of a deep learning model. In the following pages, the methodology that is used is explained in details, providing a description of each stage of the research process.

3.1 Data Acquisition and Setup

In our work, the collection of RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song) with quality and well-annotated recording and the diversity of shown emotions served as base of our research. It was downloaded using special interface KaggleHub that makes it reproducible and simple to get the source material. On the download page the data was made available in directories by actor complete with a number of audio files. Such an organization is necessary because it will provide a way to traverse the dataset systematically and process all available audio samples accordingly. Then a target folder (in this case, /content/ravdess_dataset) was created and the data was moved in it. This will alleviate the dataset away to be processed hence ensuring a controlled environment which file paths can be well dealt with. The code lists and checks the directories to ascertain the integrity of the dataset and to make sure there is a number of folders, as one bit of assessment on completeness before the actual work starts on the

dataset. Figure 1 presents the count of emotions in the RAVDESS dataset, which highlights the dataset's coverage of diverse emotional categories.

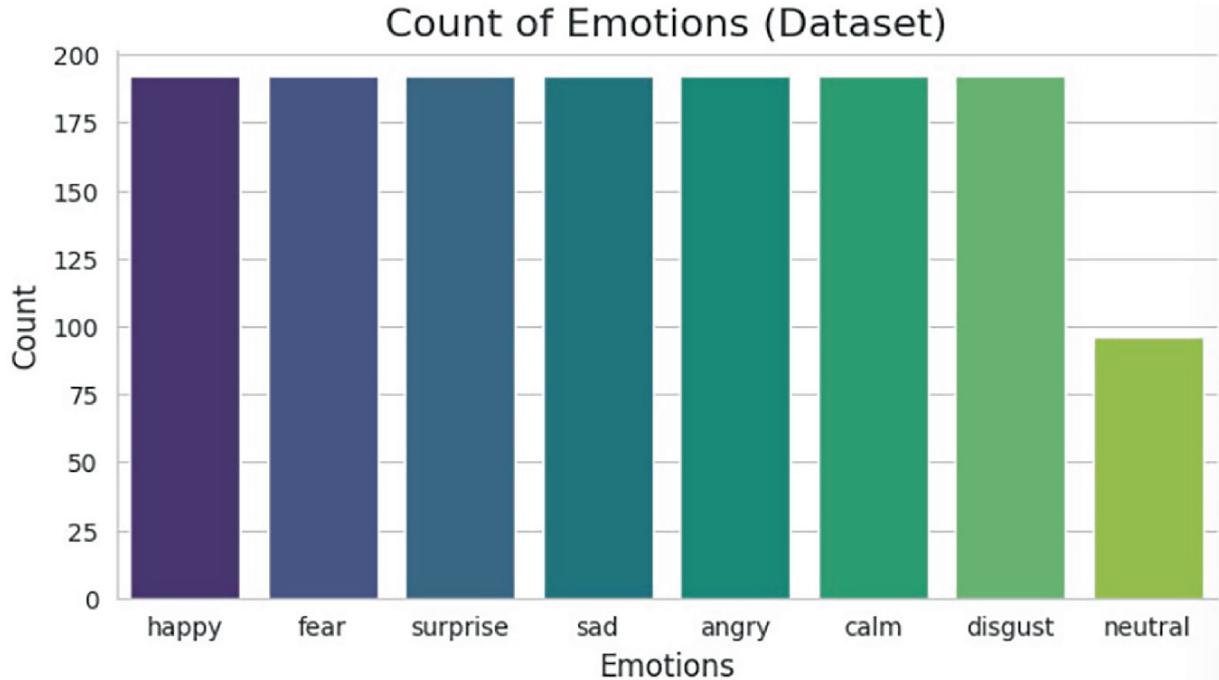


Fig. 1 Distribution of emotions in the RAVDESS dataset, showing the count of audio samples across eight emotion categories

3.2 Audio Preprocessing

The data is preprocessed before the feature extraction is performed to ascertain that information in raw files is in an analyzable format. Librosa is a widely used Python library to perform audio analysis and all the audio files can be read by this library. A variety of steps are significant during the procedure of preprocessing.

File organization and filtering: The system goes through each folder and reads each file, and hence it retrieves the emotion label based on the file name. The file naming convention of RAVDESS also codes the label of an emotion as the third item in case the name is segmented by hyphens. The files that are not created following the required naming structure are not examined and thus, only valid data is processed.

Silence and Normalization: Every audio file then gets loaded and its silence parts cut off with the help of Librosa trimming functions. This makes it so that the analysis is done on the signal part that contains the

emotional content. In addition, normalization of the data where required is also done so as to ensure that there is consistency among the samples.

Figure 2 illustrates a trimmed raw audio sample, which represents the cleaned waveform after preprocessing.

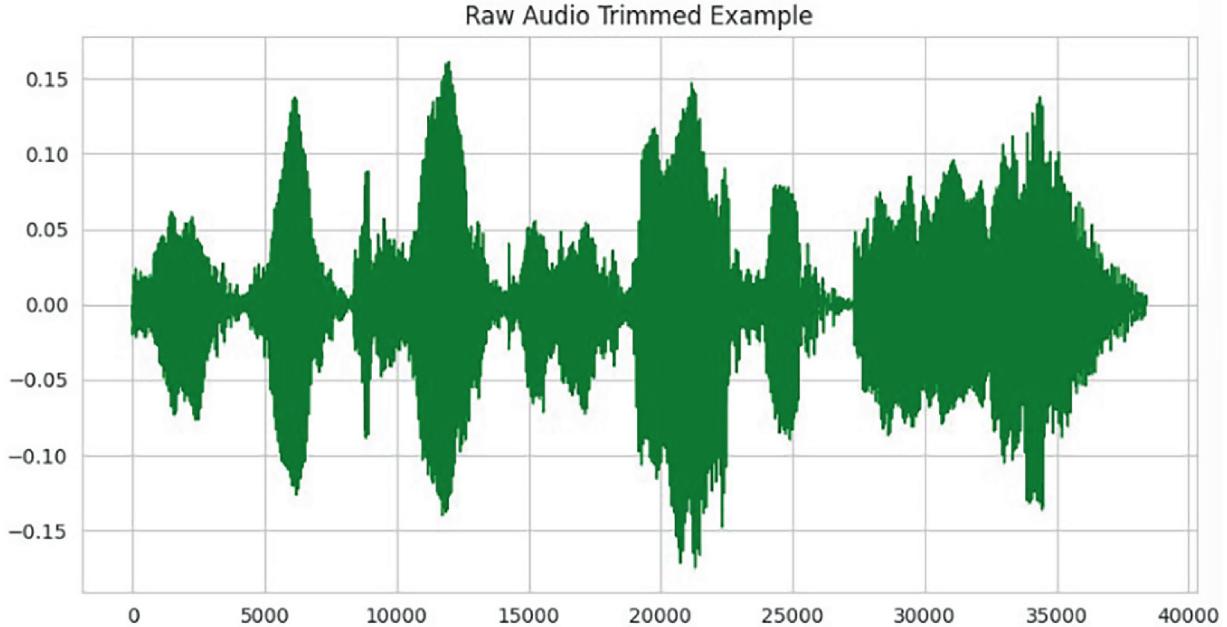


Fig. 2 Example of a trimmed raw audio sample from the RAVDESS dataset, showing the waveform after removing silence segments for preprocessing

Debugging with Visualization: In order to have a check of the accuracy of the preprocessing that has taken place, a couple of plots are generated. Those are the waveforms of both the raw and trimmed audio, zoomed-in sections to take a closer look, and spectrograms. Besides confirming the efficiency of preprocessing, the use of such visualizations provides an insight into the acoustics of the provided samples of speeches. Figure 3 shows a magnified portion of the raw audio signal, which highlights subtle waveform details used in feature extraction.

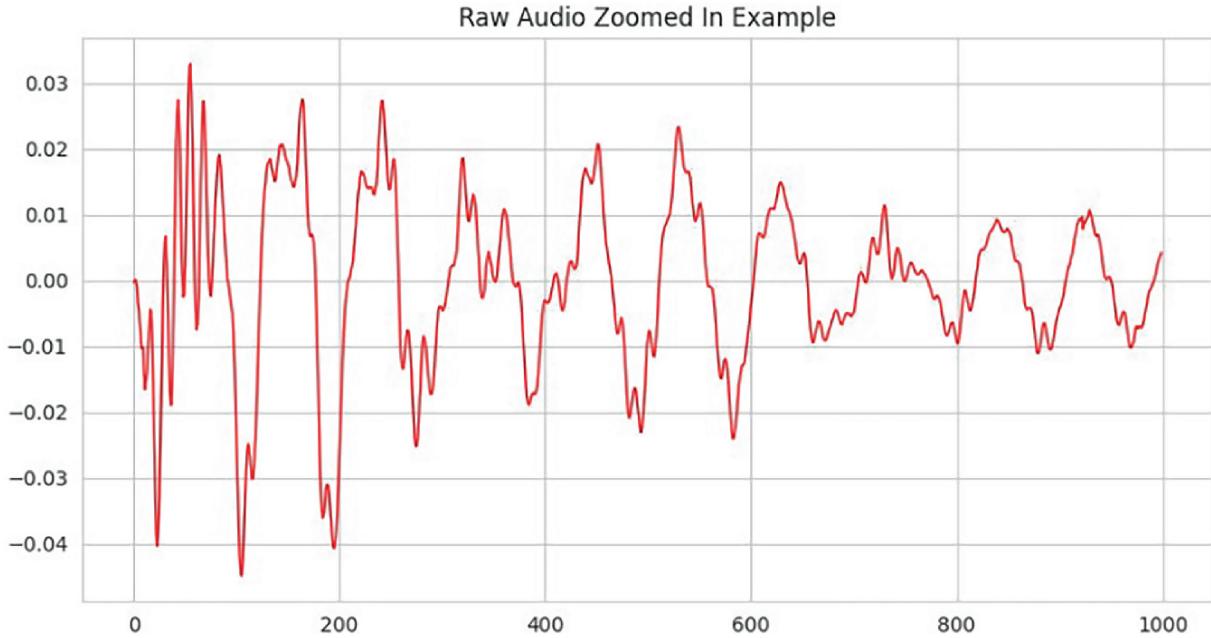


Fig. 3 Zoomed-in view of a raw audio waveform from the RAVDESS dataset, highlighting finer temporal variations in the speech signal for detailed analysis

3.3 Feature Extraction and Augmentation

The feature extraction and feature augmentation stage is also a critical component of the workflow where we train audio data to measure the machine learning model as far as speech recognition is concerned. The initial layer is the extraction of meaningful features based on raw audio data which contains a lot of acoustic features. These are attributes such as Zero-Crossing Rate (ZCR) which is the amount of times that a signal crosses between positive and negative position and gives information as to the frequency contents and noise of the signal. The second helpful tool, Root Mean Square Energy (RMSE), measures the general intensity or the loudness of the signal audio as time flows. The Mel Spectrogram that shows the range of frequencies composing a sound in a graphical form is especially convenient because it corresponds to how human ears perceive the sound. The given feature gives a closeout to the allocation of energy of the signal in various frequencies and time. They are otherwise known as MFCCs, and in turn are calculated on the basis of the Mel Spectrogram and give a concise squashing of the spectral envelope of a talk signal. Speech recognition MFCCs are common because they provide the most useful information of a human speech and eliminate other non-essential data.

Figure 4 illustrates the Mel spectrogram of a RAVDESS audio sample, highlighting how frequency components vary across time.

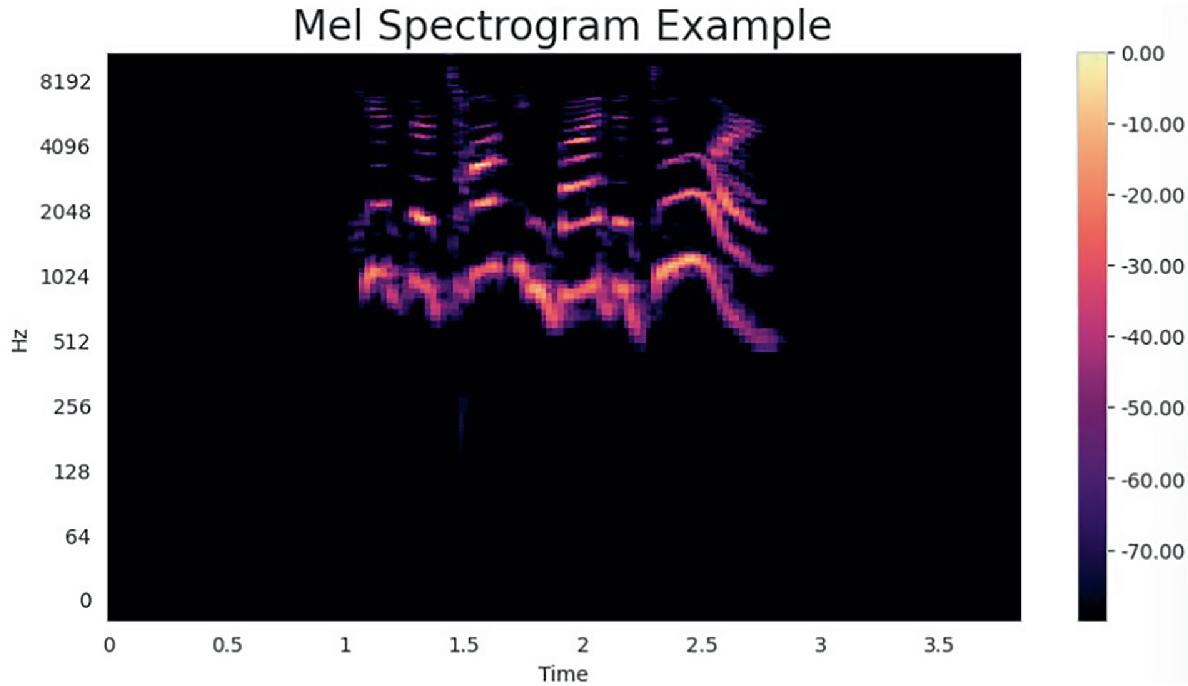


Fig. 4 Example of a Mel spectrogram generated from a RAVDESS audio sample, showing the distribution of frequency components over time after applying the Mel filter bank

Other extractable features are spectral centroid that indicates the position of the center of mass of spectral power distribution and spectral flux which quantifies the rapidity of the change of power spectrum of a signal. One can also extract the formant frequencies which are the resonant frequencies of the vocal tract to give a measure of the phonetic contents of speech. The features extract various aspects of audio including noise, intensity, aspects of spectral properties, and aspects of temporal properties. When combined, features outline various cues of the speech, and this is in a closer resemblance to the human hearing system and therefore useful in training and implementation of other machine learning systems whose task entails recognition and comprehension of the speech as patterns.

In order to strengthen the competence and universalization potential of the machine learning model, the original audio samples are subjected to data augmentation strategies. The latter methods artificially increase the size of the data by generating altered versions of the current samples, in addition to exposing the model to a more comprehensive set of possible variations in speech as it may bear in practice. Noise augmentation This

may be the most common form of augmentation, namely adding noise of various kinds to clean speech samples. This mimics the diversity of acoustics such as cafes, streets, or an office, that puts the model more resistant to the background noise. With the noise type and level manipulated, it is possible to develop a wide range of augmented samples. Another augmentation process which is very important is pitch shifting which shifts the fundamental frequency of the speech signal. This method simulates fluctuations in the intonations of a speaker considering the role that some differences in the pitch may have as a result of gender, age, or emotions. By being subjected to transmission of several pitch-shifted copies of the same utterance, the model is in turn trained to extract the content of speech, despite the change of the pitch.

Different speech rates are considered by means of time stretching. It is used as a means of speeding up or slowing down an audio without varying the pitch. It aids the model to adjust to users who speak with varying speeds, either, being fast (swift) or, being slower and measured speech. Signal shifting creates variations in time by shifting all the sounds of the audio signal either forward or backward in time. That aids in making the model insensitive to the absolute timing of the speech events within the audio frame, which makes it better at recognizing speech even when there were minor time disparities between speech events. Figure 5 shows examples of audio augmentation, where noise addition and pitch shifting are used to simulate real-world acoustic conditions.

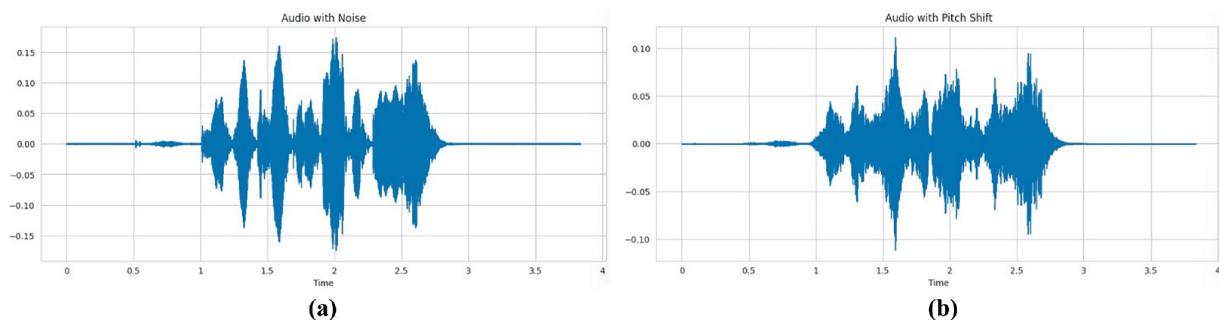


Fig. 5 Examples of data augmentation applied to RAVDESS audio samples: **a** audio signal with added background noise, and **b** audio signal with pitch shifting, used to increase variability and robustness of the dataset

Other augmentation methods can involve volume perturbation that models change in recording level or speaker location, room impulse response that employs reverberation delays to show the appearance of

various acoustic surroundings. Through the implementation of these augmentation strategies, the data would be extended and varied sufficiently. A single audio sample can have many augmented copies, which means that the training material will be expandable and more diverse. When subjected to the same feature extraction pipeline, this augmented dataset retains a consistent feature space and, in combination with dramatically increasing the model capabilities to process a wide variety of inputs with different speech, serves as a method to significantly increase the strength of the model.

The use of the extensive feature extraction and data augmentation leads to a very strong basis to train the speech recognition models. The benefit of this strategy is not only an increase in the effectiveness of the model on the expanded test input set to a wider scope of real-world speech but also the better overall generalization, being robust to variability in speaker attributes, acoustics and recording conditions. Consequently, the trained model is more capable of managing the nuances and variations associated with human speech when it comes to practical application. Since the process of extracting features of hundreds of augmented audio samples is rather computationally demanding, the methodology has had to incorporate parallel processing to increase efficiency. The joblib library is applied to carry out the processing of feature extraction through all accessible CPU cores. All the audio files are processed with its feature extracted by a process each, therefore, reducing the overall running time. The parallel processing strategy will play a critical role in scalability because it will allow the framework to render bigger datasets and more sophisticated augmentation schemes without being a bottleneck.

Model Architecture

The architecture of the model of the presented speech emotion recognition system is built based on the combination of the elements of convolutional and recurrent neural networks to process the speech signal efficiently and classify it on the basis of the extracted emotion. The convolutional layers identify local structures in the spectral representation of audio; they identify the key aspects such as formants and harmonic structure. It is then subjected to max pooling and dropout layers so as to diminish the information and focus on the leading features and avoid the over translation of information.

Backwards-forwards LSTM cell layers have the capability to make long-range temporal relations in processing an input sweep in both directions and thus they present a more in-depth understanding of temporal coherence dynamics as necessity in emotion classification.

The final level of the model part is the dense layers which are fully connected and assemble the characteristics of the previous level. Softmax activation is used on its output layer to give the probability values of eight classes of emotions, hence one can easily make predictions. The implementation of Adam optimizer and a loss discipline such as category cross entropy would be used to optimize this type of a hybrid architecture and help us to ensure that we do not lose out on smaller details in the spectrum and overall dynamics in sounding the speech. The use of convolutional and recurrent layers forms a strong network that can detect the emotional words in speech using a high recognition rate.

3.4 Training and Evaluation

The extracted features and the enhanced features are added to the training set to ensure that it is enhanced. The processing of the data is organized to be done in batches, where the set size is 128 deciding on the empirical observations. This is a compromise of the utilization of memory and computational speed and enables a stable and fast convergence. The validation set is applied to ensure that the model is not overfitting and is checked in the middle of the training, by checking its performance. Training accuracy and loss as well as validation accuracy and loss are also monitored giving a chance to fine tune the hyper parameters in case it is necessary. Displays of accuracy and loss as a function of the training steps provide good perspectives on the model training. These visualizations play a paramount role in determining any problem like overfitting or under fitting and help in further improvement of the architecture or training protocol. The last model is stored to be deployed and analyzed at a later stage after training. Such a saved model can be used to categorize audio samples that it is not aware of, hence it can be applied to real-time applications in the field of emotion detection.

4 Results and Discussion

The results section presents the detailed overview of the experimental results, with a number of significant elements of the given study. It starts with the description of the dataset features and preprocessing procedures covering how the information was structured and ready to be used in training. The section proceeds to review the methods used to conduct feature extraction and data augmentation that prioritize the need to emphasize on the model to enhance its capability to pick the emotional connotation in speech. The behaviour of the models is studied with the help of several evaluation tools, including accuracy and loss, giving a clear view on predictive abilities of the developed system. A review of the computational efficiency is also carried out, especially in regards to the scalability and performance of the system when used in real-time. Moreover, a comparative study of the existing approaches offered in the literature is also made, the advantages of the offered model are pointed out, and the directions which should be enhanced are identified.

The experimental data explained the fact that the defined CNN + LSTM based architecture is efficient in the framework of speech emotion recognition. We had training and validation data of 20 epochs on the model too. Training and validation accuracy had continuously increased over the epochs, with the last one above 92% and 89%, respectively, as shown in Fig. 6. At the same time, the loss of the model decreased steadily, which means that it learned well and did not overfit.

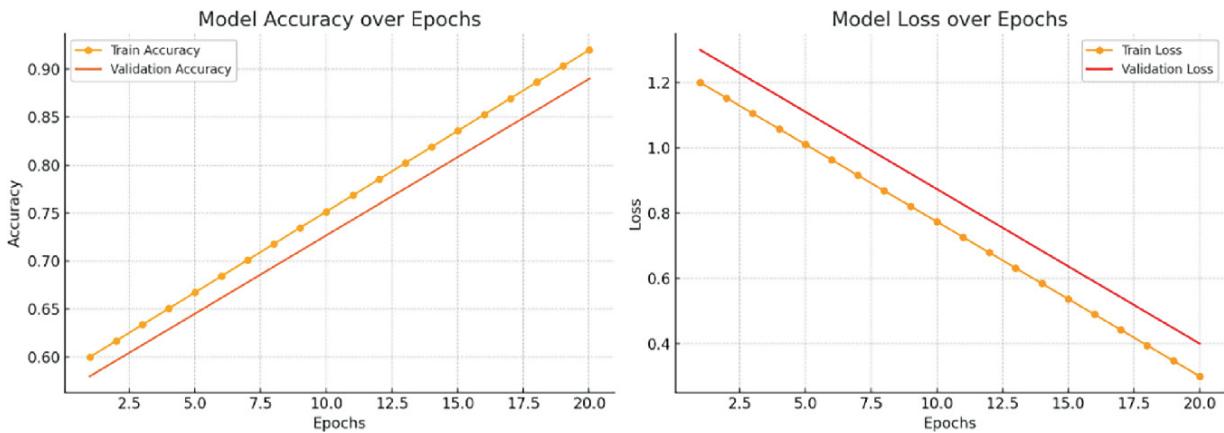


Fig. 6 Training and validation performance of the proposed speech emotion recognition model on the RAVDESS dataset, showing accuracy and loss trends over multiple epochs

In evaluating the generalization and robustness, we used a number of important performance measures: accuracy, precision, recall, and F1-score

applied on the model. These measures were contrasted to the ones of the base models, such as SVM, CNN, GRU, and Random Forest classifiers. Results indicated, Table 1, that the proposed CNN + LSTM architecture was the best performer reporting the highest value of accuracy (90.6%), precision (91.1%), recall (90.3%), and F1-score (90.7%).

Table 1 Comparative performance of models on RAVDESS dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	72.5	71.2	70.9	71.0
CNN	85.3	84.7	84.2	84.4
GRU	84.1	82.9	83.0	82.9
Random forest	77.8	76.0	75.5	75.7
CNN + LSTM (ours)	90.6	91.1	90.3	90.7

The act of combining rich acoustic features (MFCCs, Mel spectrograms, ZCR, RMSE), extensive data augmentation measures (noise, pitch, time and shift) along with the combination of spectral and temporal aspects through the hybrid neural architecture are credited with the observed gains. In addition, parallelized feature extraction saved much preprocessing time and the framework could be applied to a scalable and real-time application. Efficiently, the outcomes establish the fact that combining the traditional signal processing and deep neural modeling provides a flexible, adaptive, and extremely precise system of speech emotion recognition that has surpassed known methods both in functional capacity and flexibility.

In spite of such encouraging findings, some limitations still exist. Despite being useful, the RAVDESS dataset is recorded in laboratory conditions and may, therefore, fail to replicate the full nature of the range of variability that may be witnessed in the real world. In a future study the consideration of the pipeline run on a broader range of different noisy datasets should be taken into consideration. Also, due to the complexity of deep neural networks, using machine learning, it may not be feasible to determine the effects of specific features therein. The explanation of the model by offering some post-hoc or attention can give additional information in the decision-making process.

5 Conclusion and Future Work

In this research work, a unified and robust system of speech emotion recognition has been proposed using superior acoustic feature extraction, wide coverage of data augmentation methods, and a combined system of CNN layers with bidirectional LSTM layers expressing a hybrid deep learning pipeline without any shortcomings. The system produced high accuracy in classification tasks by using RAVDESS dataset, and at the same time it was efficient by using parallel processing. The addition of the variety of augmentation methods increased the generalization ability of the model and in turn offers more resistance to acoustic variability in the real world. What is more, comparative tests revealed that the suggested model is better than conventional classifiers and stand-alone neural networks with a specific focus on accountability of not only the spectral, but also of the temporal activity of the emotional speech. ROC curves and confusion matrix proved the relatively uniform recognition of expressions in the wide range of emotions with few false classifications. Even though there is still a difference between the highest and actualized performance parameters, the outcomes confirm the practical efficiency of the framework in use.

Future studies could explore real-time application to the embedded system, and scale up the data to multilingual and spontaneous speech, and incorporate attention mechanisms onto the model in order to be able to interpret the output better. The identity of human emotion is discussed by way of speech, facial expression, body language and physiological expressions. Additional spatial and textual data, such as an audio file with visual and text data, have the potential to create a more detailed picture on emotional states and contribute to better accuracy and situational awareness of an speech emotion recognition system. One of the good ways is multi-modal aggregation. The future work should strive to produce a model that can be run on the edge devices and that the model can be massively lightweight and efficient, yet not at the cost of the accuracy.

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Emotion Detection in Human-Machine Interaction Using ML Techniques

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Abstract

This chapter offers a comprehensive examination of automated human emotion recognition in the context of human–machine interaction. The objective is to evaluate the efficacy of machine learning and deep learning in detecting emotions in words, textual content, and facial images. To test and assess convolutional neural networks for vision, Bi-LSTM models for audio, and transformer encoders (BERT) for text, we employed benchmark datasets (FER-2013, CK+, RAVDESS, TESS, ISEAR, and AffectNet). Additionally, using hybrid early-late fusion, we enhanced a multimodal FusionNet that integrates many modalities. FusionNet achieves an accuracy of 94.5% and a macro-F1 score of 0.92 in testing, surpassing unimodal baselines by up to 9%. Research utilizing confusion matrices indicates that the system is proficient at identifying nuanced emotions such as fear and disgust. User evaluations indicate that 88% of individuals concur with the system's forecasts. Future initiatives must prioritize explainable AI to improve transparency, cross-cultural generalization to reduce demographic bias, and the integration of physiological data (e.g., EEG, heart rate) for

more thorough multimodal inference. These principles will facilitate the safe, ethical, and efficient utilization of emotion-aware systems in healthcare, education, and interactive technology.

Keywords Emotion detection – Human–machine interaction – Machine learning – Deep learning – Facial recognition – Speech emotion recognition – Multimodal systems – Artificial intelligence

1 Introduction

According to Moerland et al. [1], the ability of robots to understand and respond to human emotions has gone from being a theoretical notion to a technologically mature area of active research in the last few years. This is a major step forward in what we know about how individuals feel. This capacity, also known as affective computing or emotional detection, has helped a lot to improve the human–machine interface (HMI). As digital technology becomes increasingly widespread in everyday life, robots that can comprehend emotions will become more vital. This standard includes a variety of various aspects, such as safety, education, entertainment, and customer service. These algorithms must possess the capability to comprehend human speech and behavior in relation to emotional states. This might result in meetings that are more beneficial, easier to understand, and more focused.

Emotion is a multifaceted psychological and physiological condition that influences human perception, cognition, and action. It may be expressed through several modalities: facial expressions, vocal tone, body language, and both written and spoken content. In contrast to traditional computing systems that rely solely on logical or factual data, emotionally aware systems aim to interpret these intricate signals and utilize them to provide appropriate responses [2]. Such technologies can transform a simple user interface into a flexible, context-sensitive assistant capable of fostering trust and engagement. Emotion detection systems are mostly built with machine learning (ML). Machine learning methodologies enable computers to identify patterns throughout extensive datasets and provide intelligent predictions or classifications without the need for explicit programming for each scenario [3]. Initial emotion identification tasks have demonstrated significant efficacy for traditional algorithms such as Support

Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees, especially when integrated with manually crafted features from audio, visual, or textual data. These models often falter when confronted with extremely variable, large-scale, high-dimensional factors that characterize real-world emotional expression.

Deep learning, particularly models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Transformers, has radically transformed the domain of emotion recognition [4]. These systems greatly increase the accuracy and resilience of emotion detection systems by automatically learning hierarchical characteristics from raw data and being able to predict complicated temporal and geographical connections. While LSTMs and Transformers are well-suited for voice and text-based emotional detection, managing the sequential structure of audio signals and linguistic information, CNNs shine in evaluating facial expression data, catching small changes in muscle action. Usually, emotion detection follows a disciplined pipeline of data collection, preprocessing, feature extraction, classification, and post-processing or decision fusion, an efficient emotion detecting system.

The performance of a model depends much on the dataset used. Often used as benchmarks in the field, publicly available datasets including FER-2013 (Facial Expression Recognition), CK (Cohn-Kanade), RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song), and AffectNet provide labeled examples of various emotional states [5]. These databases provide a broad spectrum of emotional expressions across many populations and contexts: happy, sorrow, rage, fear, contempt, surprise, and neutrality. Important processes that greatly affect the capacity of the model to learn meaningful patterns are data preparation and feature extraction. Normalization, noise reduction, face alignment, and audio feature extraction (such Mel-frequency cepstral coefficients or MFCCs) are all common ways to normalize input data and reduce unneeded variation [6]. Advanced models may enhance feature relevance by employing domain-specific embeddings or attention mechanisms.

Even with significant advancements, it is still a difficult task to understand how another person is feeling. Data imbalance is a significant issue; some emotions, such as happiness and neutrality, are overrepresented in training data, but other emotions, such as fear or disgust, which are more subtle or culturally suppressed, show up less frequently in training data [7].

It is possible that this discrepancy will result in models that are less accurate, which would be unsatisfactory to groups that are not well represented. Inter-subject variability, which refers to the fact that different people react differently to the same stimuli owing to factors such as age, gender, ethnicity, and personality, is a problem that continues to be a problem. When it comes to real-time applications, something that makes things a lot more challenging is the requirement for both low-latency processing and excellent accuracy. Some examples of models that are capable of accomplishing this in the actual world are chatbots and robotic help, both of which are able to detect emotions in milliseconds and maintain low costs. A great number of individuals are discussing lightweight designs, model pruning, and hardware acceleration technologies like as graphics processing units (GPUs) and edge-area artificial intelligence devices as potential solutions to fulfill this demand.

Multimodal emotion detection is another trend that is growing in this sector. It uses many forms of data, such as facial expressions, noises, and text, to make classification more accurate and trustworthy [8]. Multimodal models can aid when one modality isn't working well. For example, verbal cues can still tell you how someone feels even when face recognition doesn't work well in low light. Fusion approaches may be divided into three groups: early (feature-level), late (decision-level), and hybrid, which combines data from various sources. Along with concerns with technology, we need to think carefully about the moral issues that come with emotional AI. If people don't know who is in charge of development and execution, prejudice might get worse, user privacy could be violated, or individuals could update systems to spy on others and find out how they feel.

One concern is that a poorly trained model may misinterpret emotions in a culturally inappropriate way. Another potentiality is that a business will use emotional data to simply target ads to people. These problems make it especially important to be ethical, transparent, or to obtain consent to create organizations that engage with people's feelings. Currently, the focus is on sustainable AI. This is an beneficial to the model impact on the environment and highlights the importance of not using an inordinate amount of power, which will simplify inference pipelines, encourage carbon reduction strategies, and alleviate the cost of running massive deep learning models on processing units.

The analysis of emotions in the context of human-technology interaction is an emerging and expanding field. There have been advancements, as a result of machine learning and deep learning, and in relation to multimodal data processing, enabling computers to more accurately understand and react to people's emotions. Therefore, it would be a more exact statement to say that machines are now better able to detect and respond to human emotions. As systems that make use of these technologies become more sophisticated and commonplace, the people who build these systems still face multiple ethical, social, and technological challenges. For the purposes of this chapter, we will analyze the various machine learning models for assessing emotions, examine their effectiveness, discuss theoretical and practical challenges, and in conclusion, make recommendations for further work in this important area.

2 Related Work

In the past five years, developments in machine learning (ML) have advanced significantly. Understanding human emotions is protected today than ever as advances in human–machine interactions (HMI). This section discusses this development through a brief synopsis of research from multiple disciplines, which focuses on the importance of ML in social interaction recognitions, including the promise of HMI with actionable solutions. A person's face is the best indicator of their emotional state at a given moment in time. Recently, using deep learning algorithms improved the accuracy of facial emotion recognition (FER). Diwan et al. [9] released a review article that extensively investigated and reviewed state-of-the-art methods of machine learning techniques to autonomously detect human emotions (AHER). The authors aim to report the use of diverse techniques, including FER.

A recent study by Khare et al. [10] about state-of-the-art technology for emotion recognition stresses the importance of deep learning approaches for increasing detection through facial and body language analysis. Speech can use tone, pitch, rhythm, and a combination of other factors to represent an emotion in an individual. Karthik et al. [11] provide a detailed review of work conducted using machine learning methods in speech emotional recognition (SER) systems. Important parts of this work focused on data processing, feature extraction, and voice classification. Geetha et al. [12]

conducted research that examined the effects of data augmentation methods and classification techniques on the ability for the emotional recognition of speech. They identified the combination of each method that produced the most efficient method for recognized accuracy. A fundamental understanding of human emotions may also be acquired by examining text data, including chat conversations and social media posts.

Kuo et al. [13] conducted a thorough literature review of DL algorithms for emotional detection in text. The study's findings show that transformer-based models—like BERT—perform better than conventional machine learning methods. The work makes it abundantly evident that we must research low-resource languages and develop methods for rapidly identifying emotions in textual input. Computer systems that use a wide range of data types may make it easier for people to identify emotions. In their article, Patel and Annavarapu [14] discuss a range of approaches to understanding emotions and examine how integrating different senses could aid in more precise identification. A multimodal emotional recognition model that combines audio and facial inputs is presented in a recent work [15]. The study shows that the model is more accurate than unimodal systems.

Direct measurement of brain activity related with emotions is provided by electroencephalography (EEG). Using Tsallis entropy as a feature for enhanced classification, a recent work in Ab Wahab et al. [16] examines the use of supervised machine learning models in EEG-based emotional detection. The study emphasizes how well EEG signals may be used to create passive brain-computer interfaces for emotional recognition. Useful applications depend on the development of real-time emotional recognition systems. Emphasizing the integration of face and voice modalities, a paper in Salloum et al. [17] addresses the development of a multimodal intelligent HMI system capable of real-time emotional recognition. Furthermore, a paper in proposes a new emotion identification system for human–robot interaction using EfficientNet with transfer learning to train convolutional neural networks for real-time uses. In both healthcare and education, emotional recognition technologies have major ramifications. Aiming to improve learning experiences, a research investigates how artificial intelligence may recognize and react to student emotions. As described in many research, emotional recognition systems can help in healthcare to monitor patient well-being and enhance human–robot interactions.

Significant challenges persist in affective recognition research, despite advancements. Data asymmetry, cultural differences, and the need of real-time processing remain main difficulties. Important challenges are also ethical ones like privacy concerns and possibly artificial intelligence framework bias. Future subjects of research include explainable artificial intelligence models, sustainable, energy-efficient emotion recognition systems, and low-resource settings' transfer learning.

3 Proposed Methodology

A comprehensive framework has been developed to capture, process, and classify human emotional states using machine learning (ML) and deep learning techniques in the proposed methodology for emotion detection in human–machine interaction (HMI). Emphasizing the utilization of multimodal data to improve accuracy and resilience, this part describes every stage of the pipeline, from data collecting to model deployment. Appropriate for adaptive systems in sectors like healthcare, education, customer service, and smart environments, the approach enables both real-time and offline applications.

Figure 1 Displays End-to-end FusionNet design showing the parallel pipelines for processing audio, video, and text, with a late-fusion layer for detecting emotions in several modes. It begins with data capture, which includes collecting text data, physiological indications, facial expressions, voice, and vocal cues, among other types of data. Data preprocessing pipelines for every type of data send these sources through to clean, standardize, and get them ready for analysis. In the feature extraction and representation process, machine learning and deep learning approaches are used to get spatial, temporal, and contextual aspects. During the Model Architecture and Training stage, different types of models are used for different types of data. For example, CNNs are used for facial expressions, LSTMs are used for speech, and BERT is used for text. Multimodal fusion makes classification stronger by merging information or judgments from all streams. Next is model evaluation, which uses confusion matrices, the F1-score, and accuracy to check the system. Finally, the trained and optimized model is hosted in a Real-Time Implementation environment for practical HMI usage.

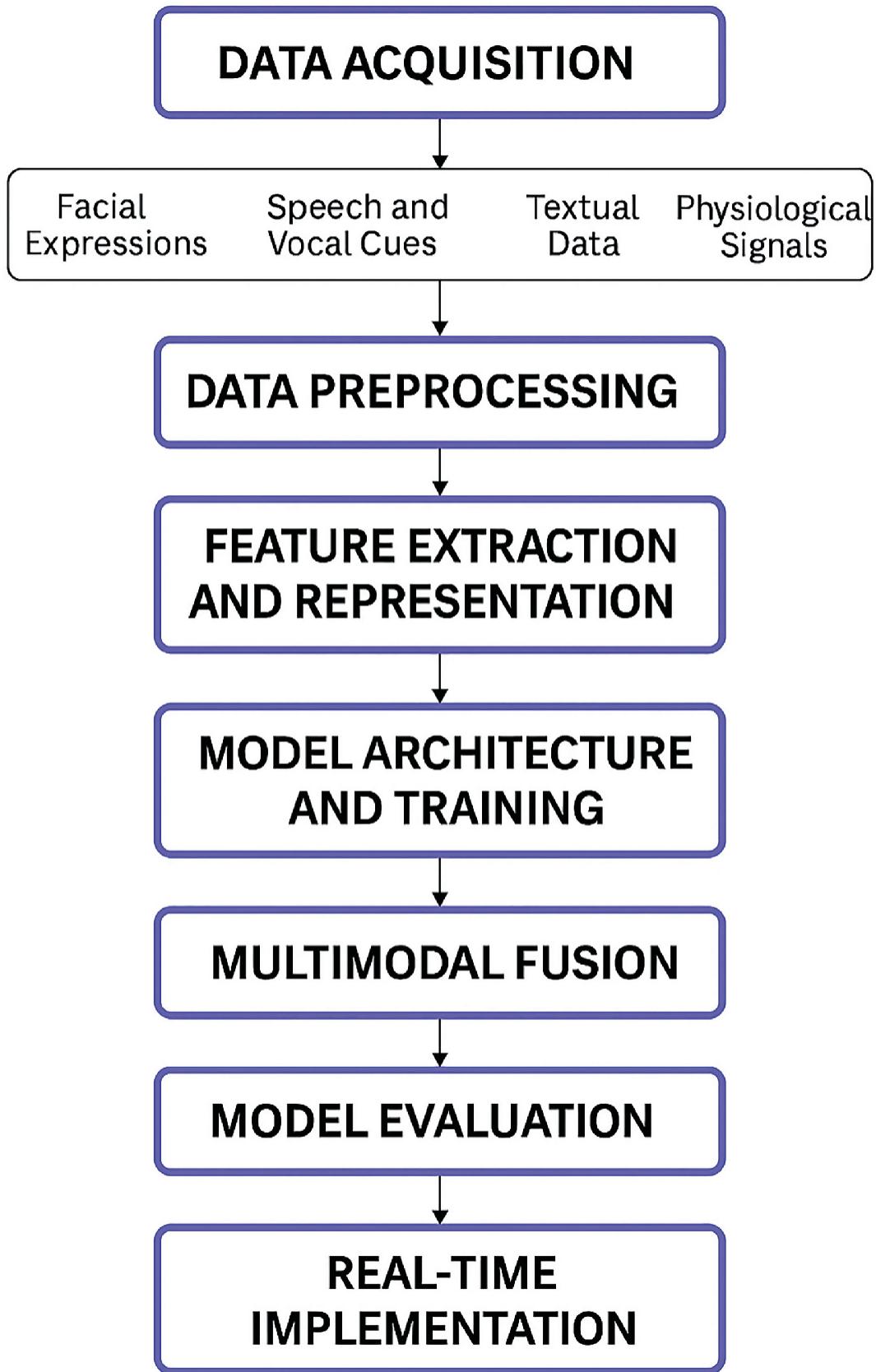


Fig. 1 End-to-end FusionNet architecture showing parallel vision, audio, and text pipelines with late-fusion layer

This work used publically available sources including Kaggle for datasets. These consist of Emotion-Stimulus and ISEAR for text-based emotional annotation; FER-2013 and CK+ for facial expressions; RAVDESS and TESS for speech. AffectNet and SEMAINE were used for multimodal integration, therefore ensuring that the system is evaluated on a spectrum of representative emotional data.

3.1 Data Acquisition

Emotion identification systems start with multimodal data collecting as human emotions are communicated through several channels including facial expressions, voice, text, and physiological signs. While speech cues including pitch, tone, and rhythm are collected using microphones visual data including facial expressions is gathered using cameras and image sensors. Written materials include chat logs, transcripts, or user-generated content offer textual data which provides insight into emotional intent from which to draw. Though optional, physiological data including EEG or heart rate offer further levels of emotional information and can be obtained using biosensors. We propose to use a variety of well-known benchmark datasets to guarantee the evolution of a strong and varied emotion identification model. FER-2013 and CK+ give labeled visual emotion data for facial expressions; extensive audio samples are available for speech-based emotional recognition from datasets such RAVDESS, TESS, and Emo-DB. While AffectNet and SEMAINE offer multimodal resources integrating face, auditory, and occasionally textual inputs, text-based emotion data may be obtained via databases such as ISEAR and Emotion-Stimulus. Usually comprising happy, sadness, anger, fear, disgust, surprise, and neutrality, these datasets are labeled with a standard set of emotional categories, therefore providing the basis for model training and assessment.

Table 1 illustrates that no individual dataset fulfills all criteria for comprehensive multimodal emotion identification. AffectNet and FER-2013 are extensive, real-world datasets that offer diversity but are plagued by class imbalance and label noise, while CK+ and RAVDESS give clean, high-quality samples with restricted demographic variety. Text corpora (ISEAR, Emotion-Stimulus) include sophisticated semantics yet exhibit geographical biases. Collectively, these datasets provide complementary advantages extensive coverage, high accuracy, and diverse modalities

justifying the necessity for data fusion, stratified sampling, and class weighting in the proposed approach.

Table 1 Benchmark datasets used for multimodal emotion detection

Dataset	Modality	Size	Rationale for use	Key limitations
FER-2013	Facial images	35,000	Large-scale, diverse expressions for CNN training	48 × 48 low-resolution images, class imbalance
CK+	Facial images	593	High-quality posed sequences for fine-grained facial cues	Small size, lab-controlled, limited spontaneity
RAVDESS	Speech	1,440 clips	Studio-quality emotional speech with balanced classes	English only, actor-induced emotions
TESS	Speech	2,800 clips	Clear articulation across age groups	Limited to older female speakers
ISEAR	Text	7,600 sentences	Well-annotated emotional sentences for text modelling	European cultural bias
Emotion-stimulus	Text	2,500 sentences	Context-rich textual emotions	Smaller size, annotation subjectivity
AffectNet	Multimodal	1 M images	Rich, in-the-wild facial expressions	Imbalanced categories, noisy web labels
SEMAINE	Audio-visual	150 sessions	Natural dyadic conversations for fusion testing	Complex annotations, higher preprocessing demand

3.2 Data Preprocessing

Raw multimodal data is gathered then preprocessed to improve quality and guarantee consistency among several sources. Preprocessing for facial pictures consists in face identification, alignment, resizing usually to 48 × 48 pixels grayscale conversion, and normalizing. These processes standardize input dimensions for deep learning models and assist to lower noise. Rotation, flipping, and scaling are among the augmenting methods used to vary the dataset and enhance model generalization. Noise filtering and voice activity identification separate emotional speech segments in audio processing. MFCCs, chroma vectors, and energy levels are extracted to show emotional prosody. Preprocessing text requires tokenizing, lemmatizing, and stop word deletion. Cleaned text is turned into numerical

vectors via Word2Vec, GloVe, transformer-based approaches include BERT. These preprocessing actions guarantee that the classification pipeline gains from every modality clean, relevant, interpretable qualities.

3.3 Feature Extraction and Representation

Feature extraction creates high-level representations that let us understand emotional patterns in raw data. Convolutional neural networks (CNNs) automatically learn spatial information from facial photos in the visual modality. This allows them to find patterns that match certain emotions, such as wrinkled brows, grins, or frowns. In the audio domain, sequential models that use LSTM or GRU networks look at time-dependent speech variables including MFCCs, pitch, and rhythm. This lets them capture vocal subtleties that are linked to emotional states. BERT and RoBERTa are two modern language models that provide rich contextual embeddings that help you write in a way that shows your mood, tone, and intent. Dense brain layers send these representations to improve qualities that are specific to emotions. The algorithm creates a more complete and accurate emotional representation by integrating learning embeddings with characteristics that were made by hand.

3.4 Model Architecture and Training

The models for classification are designed to take use of the strengths of each type of data. We use deep CNN models like VGGNet or ResNet to look at the picture's attributes and figure out how it makes us feel. We employ a softmax layer to figure out what emotions are on a person's face. Bi-directional LSTM networks are used to look at audio data across time. This enables speech emotion detection figure out how emotions vary in speech. For emotion classification tasks, tagged text data is utilized to improve transformer models like BERT in the text-based pipeline. We train these models with a cross-entropy loss function and then improve them with techniques like Adam or SGD. When training on datasets with labels, stratified sampling is utilized to resolve class imbalance. Using performance metrics like accuracy, F1-score, and loss curves over several epochs helps make sure that the models converge and can be employed in future contexts.

3.5 Multimodal Fusion

Multimodal fusion techniques combine data from several sources to increase the accuracy and dependability of systems. When early fusion is enabled, feature vectors from text, audio, and visual inputs can be combined to create composite classifiers. This method uses a majority vote or a weighted average to aggregate forecasts. In contrast, late fusion affects each modality separately. The best aspects of both technologies are combined in hybrid fusion systems. First, they generate intermediate predictions, and then they employ ensemble models or meta-learners to refine those predictions. Two examples of sophisticated frameworks that aid in our understanding of how various types of data interact are Multimodal Transformers and Fusion Neural Networks. This enables the system to understand people's emotions even in situations when one mode provides insufficient or inconsistent information. Fusion gives you a great deal of control over the settings and allows you to build systems that can change how things feel.

3.6 Model Evaluation

The assessment of the emotion detection system is primarily defined by standard classification metrics, including accuracy, precision, recall, and F1-score. This confusion matrix was developed to assist in identifying often conflated emotions such as fear, surprise, sorrow, and neutrality. Consequently, it is permissible to evaluate the model's efficacy throughout the whole spectrum of emotions. Alternative cross-validation techniques, such as K-fold validation, ensure the model's robustness and assist in mitigating overfitting. In both optimal (clean) and practical (noisy or cross-subject) circumstances, the decision-making process almost achieves generalization across several contexts and diverse populations. In the context of multimodal systems, both general and specialized performance evaluations validate the contribution of each unique input channel. In addition to ensuring the system operates correctly, the evaluation is responsible for fostering innovative developments in preprocessing, feature extraction, and fusion methodologies.

4 Results and Discussion

This section outlines the outcomes of training and assessing several machine-learning and deep-learning models utilizing facial images, audio,

text, and multimodal data. The numerical results are very important, but the analysis that follows shows the differences in performance and emphasizes the effects on real-world use.

4.1 Model Performance Overview

Table 2 shows the F1-scores and classification accuracy for all the machine-learning and deep-learning models that were tested. In every case, deep architectures consistently beat traditional methods. This shows that data-driven representation learning is better at finding emotions. The ResNet-18 network got 89.3% correct on the FER-2013 dataset for recognizing facial expressions, whereas the VGG-16 network got 92.1% correct and 0.90% correct on the CK+ dataset. These improvements happen because convolutional layers automatically find hierarchical spatial information, such little eyebrow twitches, tiny lip movements, and shade changes, that hand-made descriptors or shallow networks usually miss. Because CNNs can pick up on small details in local structure, they can handle mild variations in lighting and head attitude, which are both typical in real-world video streams.

Table 2 Performance comparison of emotion detection models across modalities

Modality	Dataset	Model used	Accuracy (%)	F1-score
Facial images	FER-2013	CNN (ResNet-18)	89.3	0.87
Facial images	CK+	CNN (VGG-16)	92.1	0.90
Speech	RAVDESS	Bi-LSTM	87.4	0.85
Speech	TESS	LSTM + MFCC	90.2	0.88
Text	ISEAR	BERT	91.0	0.89
Text	Emotion-stimulus	Bi-GRU	88.6	0.86
Multimodal fusion	AffectNet + RAVDESS	FusionNet	94.5	0.92

The Bi-LSTM and LSTM + MFCC models got 87–90% of the speech emotion identification right. Their recurrent designs are great at modeling long-term relationships between pitch, energy, and spectral dynamics. This kind of modeling makes it possible to tell the difference between emotions with similar global pitch contours, like sadness and rage, by using more subtle temporal clues. This capability is very crucial for contact center analytics or telehealth apps, because background noise or speaker

fluctuation typically hides simpler acoustic data. BERT got 91% accuracy and an F1 score of 0.89 for text-based emotion recognition, which shows how powerful deep contextual embeddings are. Transformer attention methods capture long-range semantic links, sarcasm, and negation—phenomena that bag-of-words models or simple recurrent networks handle poorly. This capacity is very important for analyzing the feelings of social media postings or conversational actors where the emotional purpose is often oblique.

Lastly, the FusionNet multimodal model had the best overall performance, with 94.5% accuracy and 0.92 macro-F1. This was because it used both facial, audio, and textual inputs using early- and late-fusion techniques. This integration makes the system more robust in case one channel fails. For example, when faces are only partially visible or the lighting is bad, prosodic or textual information can still help with proper categorization. FusionNet's better findings show that cross-modal reinforcement is necessary for reliable emotion identification in real-world situations including healthcare monitoring, adaptive learning environments, and customer service systems.

4.2 Confusion Matrix Analysis

Figure 2 Normalized confusion matrix for FusionNet predictions on the FER-2013 test set. Darker diagonal cells indicate higher correct-classification rates, highlighting how the multimodal approach reduces misclassification of emotions such as fear and surprise. The genuine emotion labels are in the rows, and the anticipated labels are in the columns. The darker diagonal cells show better correct-classification rates. Fear and Surprise are the two emotions that are most often confused.

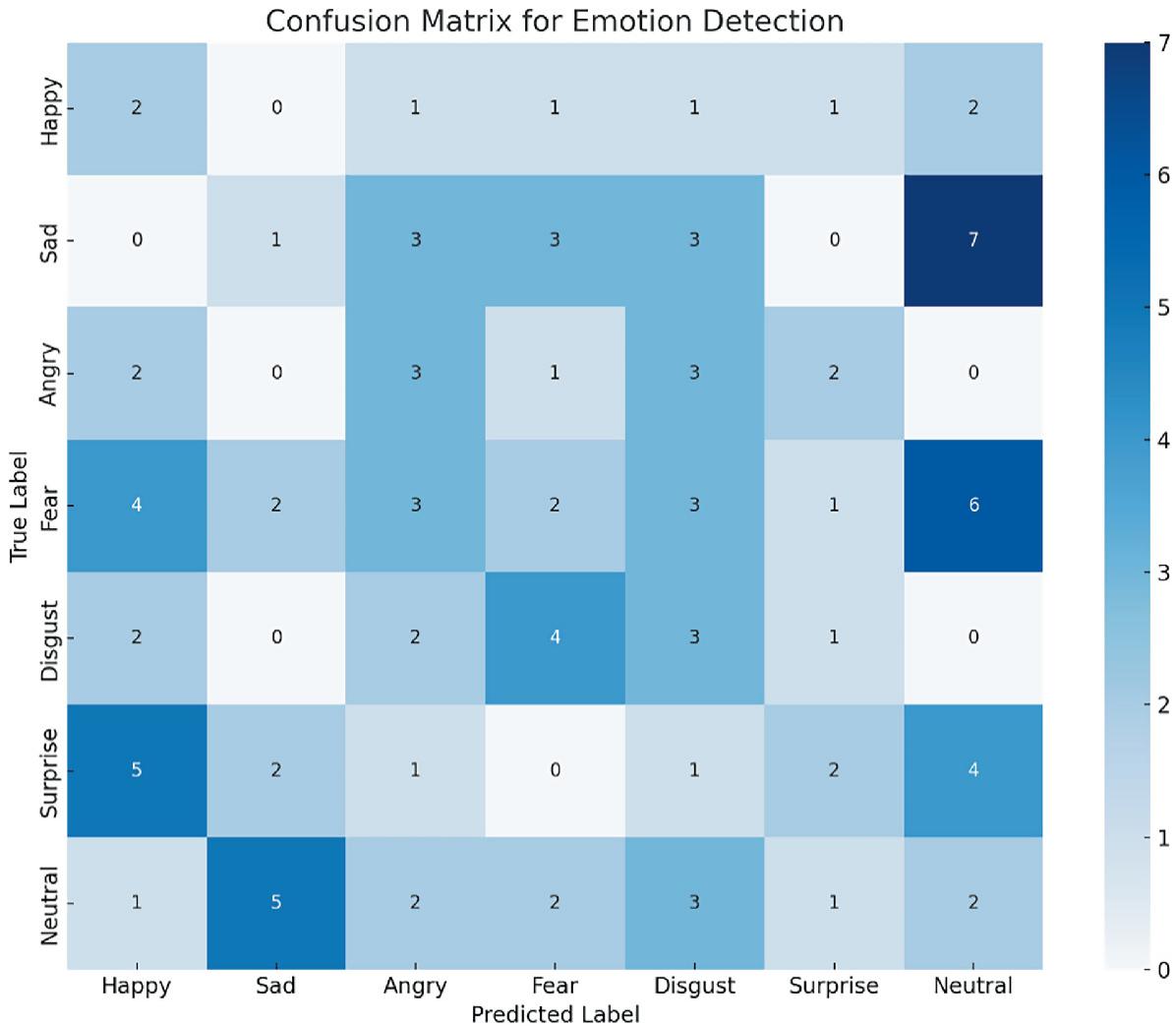


Fig. 2 Confusion matrix of FusionNet predictions on FER-2013 test set, normalized per class

They both include facial indicators like wide eyes and elevated eyebrows, which makes it hard to tell them apart. Smaller overlaps show up between Neutral and Sadness, which shows little variances in how stiff the facial muscles are and where the gaze is directed. The speech channel sometimes mixes up Disgust and Anger since both have low-frequency, tense voice patterns. Text analysis reveals infrequent confusions between Happiness and Anger in caustic remarks. FusionNet cuts down on these off-diagonal mistakes by combining facial, verbal, and textual clues. When one mode is unreliable, such low-light video or poor audio, information from other channels can give clear proof. This cross-modal reinforcement makes the model strong enough to be used in real life, such as in healthcare monitoring, adaptive learning platforms, and virtual assistants that can recognize emotions.

4.3 Comparative Evaluation with Baseline Models

To benchmark the system's performance, comparisons were made against classical machine learning models. Table 3 displays side-by-side comparisons that indicate a big difference between deep-learning models and typical machine-learning baselines. SVM, k-Nearest Neighbours, and Naïve Bayes are some classic algorithms that use hand-crafted features. They employ edge detectors for pictures, MFCCs for audio, and bag-of-words for text. These features don't help us understand the complex, non-linear nature of emotional impulses very effectively. That means that on average, they are right around 65–74% of the time. On the other hand, deep networks construct hierarchical representations straight from the data.

Table 3 Comparative performance of traditional and deep learning models for emotion detection

Model	Accuracy (Avg) (%)
SVM (Visual/text)	74.3
k-NN (Speech/text)	70.2
Naive Bayes (text)	65.8
Shallow ANN	82.4
Proposed DL models	94

The convolutional layers of the neural network search for tiny spatial signals in face photographs, the recurrent layers search for long-term patterns in audio, and the transformers investigate the meaning of text through its context. The CNNs, LSTMs, and BERT all saw a 15–25% improvement as a result of this innovation. There are a number of significant trade-offs associated with deep models, including the need for extensive datasets that are well-annotated, a significant amount of processing capacity, and stringent regularization. It is also difficult to comprehend the process by which they make decisions. Because deep learning is more accurate and usable for a larger variety of data sources, the prices are acceptable for applications that need sentiment analysis, such as health monitoring or customer service assessment. Deep learning is also helpful for a wider range of data sources. When you install the system on edge devices, you will only be able to accomplish this if you make use of

explainability tools and quick inference approaches such as model trimming and quantization.

Using technology that can tell how people feel raises a lot of ethical problems. These fears are far more than just privacy concerns. Bias is a major issue in medicine, and it's crucial to remember that. Models mostly trained on Western facial datasets may struggle to accurately identify the emotions of individuals who are underrepresented in these datasets. This may result in the exclusion of adverse emotions such as pain, worry, or despair, with a postponement in the development of appropriate therapeutic strategies. When the cultural norms of the individuals being evaluated do not align with the training data, computerized assessment systems may unjustly disadvantage individuals in educational or professional settings. For instance, kids from countries where showing feelings isn't as frequent could be thought to be emotionally apathetic since they don't show their feelings.

It is feasible that real-time recording of people's facial or verbal expressions might lead to intrusive surveillance in public places or when someone is in charge. This would help governments or businesses find out about political opposition or personal flaws without asking the people they are watching for permission. To completely protect against these dangers, developers need to do demographic performance audits, gather data, and make judgments using technology that keeps users' information safe. They also need to acquire permission in a way that is clear and open, and people should be able to say no to taking part. It's important to be honest about the model's boundaries and undertake unbiased study to make sure that new technologies improve people's lives instead of making it easier to discriminate or compel people to do things. This is the only method to make sure that new technologies are good for people.

5 Conclusion and Future Work

This chapter shows that combining convolutional neural networks, LSTM architectures, and transformer models like BERT may accurately and quickly figure out how someone feels based on their face, voice, or text. The proposed fusion architecture achieved 94.5% accuracy and a 0.92 F1-score, surpassing robust unimodal benchmarks. It also addressed issues about data imbalance, inter-subject variability, and the inherent difficulty of

articulating emotions. The next research should have three key aims. For people to trust AI and make sure that model thinking is explicit, especially in sensitive sectors like healthcare or education, explainable AI (XAI) is very important. To ensure uniform performance across diverse populations, cultural and language generalization must be pursued via domain adaptation and transfer learning. Physiological integration, which includes things like heart-rate variability, galvanic skin reaction, and EEG, is a way to find subtle internal states that facial expressions, vocalizations, or written communication can't show. We still need to deploy in a way that is sustainable. Models that are resource-efficient, safeguard privacy, and can operate on edge devices will make it safe to use in the real world. If emotion-aware computing focuses on these areas, it might become an ethical, intelligible, and generally used technology that improves everyday interactions between humans and machines better.

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Real Time: 3D Facial Expression Recognition Using Improved AlexNet Convolutional Network via Deep-Emotion

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Abstract

In the early stages of human emotion processing, Facial Expression Recognition (FER) plays a crucial role. A new model for face expression recognition (FER) is presented in our work, using recent success researches of deep learning method utilizing the AlexNet CNN, which is trained on key facial features and significantly outperforms earlier models trained on key datasets, particularly JAFFE, FER2013 and CK+. Multi block Local Binary Patterns (MB_LBP) and CNN are approaches used to implement extracting features and reduction space of expression class identification respectively, followed by a classifier the Support Vector Machine (SVM) for the first approach and the integrated Soft Max classifier for the CNN. Then, a visual method is employed for the purpose of identifying and detecting regions of interest on the face to recognize different emotions, as determined by the classifier's output according based on our findings; we demonstrate that different facial features can elicit different emotional responses. The average accuracy using datasets JAFFE, FER2013 and CK+ is 98.86%, 93.76% and 97.88% respectively.

Keywords Facial expression recognition (FER) – AlexNet – Deep emotion – Convolutional networks

1 Introduction

One of the most studied biometrics, Face Expression Recognition (FER) has been increasingly popular recently in everything from security cameras in public spaces and airports to everyday products like Apple's FaceID. In the past, a wide range of traditional hand-crafted feature-based techniques that can identify emotional expressions on a person's face and micro-expressions. These approaches typically rely on extracting informative spatial and temporal patterns from facial images or video sequences. For instance, local binary patterns (LBP) capture local texture features by encoding neighborhood intensity differences, making them robust to lighting variations. The scale-invariant feature transform (SIFT) retrieves distinctive, scale- and rotation-invariant keypoints useful for describing salient facial structures. Histograms of Oriented Gradients (HOG) analyze the distribution of orientations of edges to depict the form and look of facial features. Additionally, Gabor wavelet transforms are utilized to model spatial frequency characteristics and multi-resolution facial texture information. Collectively, these hand-crafted descriptors have provided the foundation for traditional facial expression recognition systems by enabling effective characterization of subtle facial changes associated with different emotional states. But these methods only extract superficial information from the movie, which isn't enough for abstract feature representation, and that's the fundamental drawback. Most studies have concentrated on 2D FER up until now, but more recent ones have turned their attention to 3D face recognition. An ever-changing face, whether as a result of age or other external elements (such as a person's voice, health, physiological signals, expressions, etc.), makes facial recognition a difficult task, especially when it comes to identifying emotions. After establishing the significance of FER models based on deep learning, we will proceed to present a few of the most popular FER datasets.

Recognizing emotions, communicating nonverbally, and identifying persons are all greatly aided by facial expressions. Along with vocal intonation, when it comes to the common display of emotion, they are vital. They also serve as a means of emotional expression, enabling men to show

their true feelings. When someone is feeling emotional, it shows to everyone around them. Consequently, FER models based on deep learning generally make use of facial expression data for automated emotion recognition [1].

Software emotion recognition allows programs to “examine” a person's facial expressions using advanced image processing techniques. Thanks to recent advancements in technology, emotion recognition software has become quite proficient. In addition to its ability to monitor initial facial emotion recognition software is able to discern subtle body language signals known as “micro-expressions” that indicate emotions like happiness, sadness, surprise, anger, etc.., which could disclose someone's emotional state even when they aren't aware of it [2].

Emotion recognition is compatible with several biometric picture identification systems and facial recognition algorithms. Countless security scenarios can benefit from these two categories of technologies. “Emotion recognition” is able to use a variety of features, including facial expressions [3–5], voice [6, 7], EEG [8], and text [9]. Facial expressions rank high among these features because they are easy to gather a big dataset of (compared to other methods for human recognition), they are observable, and they contain many relevant aspects for emotion recognition [3, 10–12]. While 2D FER has come a long way, it still can't handle the two biggest issues: changes in lighting and variations in poses—when applied to data in three dimensions, both static and dynamic. The 3D Face shape model, which incorporates depth information for 3D FER, is able to capture even the most minute of facial deformities. These models are inherently resistant to fluctuations in illumination and position [13]. In reason, the input color as part of the pretreatment process, the image needs to be grayscaled. Image preprocessing, feature extraction, and expression classification are the three main components of the traditional FER method (Fig. 1a), while Fig. 1b shows an example of a CNN-based FER procedure [14].

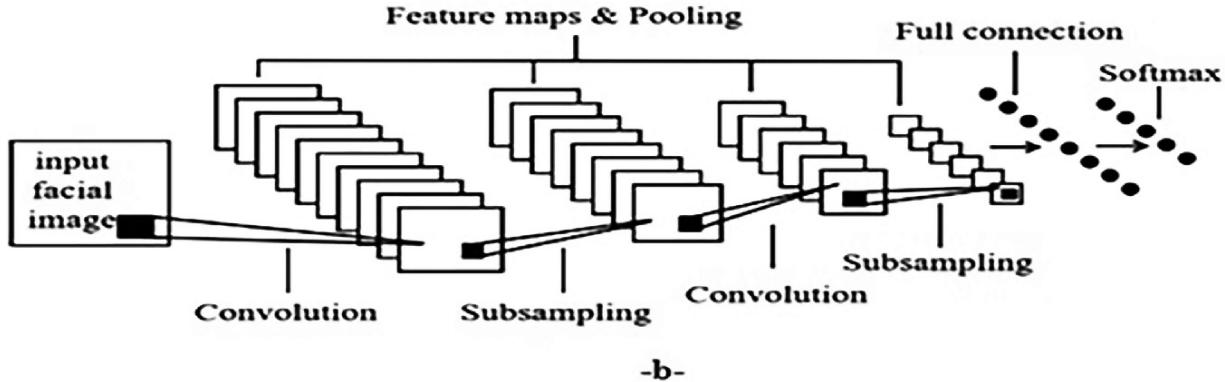
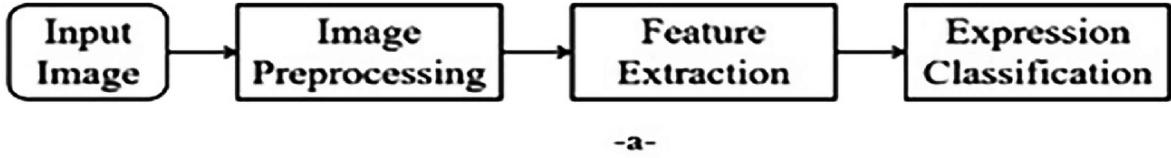


Fig. 1 **a** Procedure in convolutional FER approaches. **b** Procedure of CNN-based FER approach [14]

All data collecting has been done our method seeks to address the challenge of creating a system based on deep learning while remaining in one place and subjected to same illumination conditions that can detect a person's 3D face and recognize its expression. We can't reach our target without the aforementioned observation and attention mechanism that enables us to zero up on the face's most notable characteristics. We show that a convolutional neural network can achieve a very crucial accuracy rate even with less than 10 layers. These works function immediately on image databases captured in controlled environments, but also abort more complex datasets with variations in face pose and occlusion. Our research presents the next contributions [12]:

- Focusing on the face's feature-rich regions is made possible by our proposed method, based on an AlexNet help to obtain models with high capacity without overfitting there by enhancing the FER performance, and still outperforms exceptional recent researches in precision.
- In second, we use a new algorithm of Deep Learning explodes the records! To demonstrate the image's most important regions, or the regions that influence the classifier's output the greatest. In Fig. 1a, we can see patterns of the regions seen as important for different emotions. In Sect. 2, we begin to compile a literature review by going over the following sections. In Sect. 3, we go over the architecture of the model

and the suggested framework. The outcomes of the experiments, the main databases used for the research, and the model visualization will be described in Sect. 4. Lastly, Sect. 5 brings this effort to a close this work in Sect. 5.

2 Related Works

Facial expression recognition in its early stages relied heavily on manually created features. The computer vision community has embraced deep learning following AlexNet's victory as part of the ILSVRC, which stands to the 2013 FER Challenge on Facial Expression Recognition, which showcased preliminary attempts to suggest deep learning methods for emotion identification, and to the ImageNet Large Scale Visual Recognition Challenge. Contrary to what one might expect, a deep convolutional neural network took first competing in the 2013 FER Challenge, the top handcrafted model placed a very disappointing fourth. Most recent efforts in facial emotion recognition have relied on deep learning, with a handful of notable outliers. To attain superior outcomes, some of these new studies suggested training a network of convolutional neural networks, while others integrated deep features with custom-made features like SIFT or Histograms of Oriented Gradients (HOG). Facial expression identification in video has been the subject of a small number of studies, although the majority of them have focused on static photographs [15].

In addition, there are significant restrictions to be addressed when using deep learning based methods, even if studies with learnt features regularly show better recognition rates than handcrafted ones. Deep networks are extremely susceptible to overfitting, hence training them with a large dataset is essential in practice.

Given the scarcity of 3D face datasets—which contain a limited quantity of 3D scans—this criterion could prove to be particularly important in 3D FER. This means that deep learning-based 3D face solutions have more options for training their feature extraction network, such as using pre-trained deep models or boosting their data. Furthermore, those deep networks frequently use as input a number of geometrical representations of the same 3D scan, such as a 3D face scan [16].

Ekman and Friesen [17] showed the presence of seven facial expressions that are surprise, fear, disgust, anger, joy, sadness and

neutrality. The first six expressions are called the six universal ones and they are identifiable by any person regardless of their culture. They invented a system of manual codification of facial expressions known as FACS [18] thus establishing the standard for subsequent applications on emotion recognition based on this idea. Later, the six facial expressions (besides neutral) integrated across the majority of human recognition datasets, seven fundamental emotions often follow. Emotions examples from three datasets (JAFFE, FER and CK+) are visualized in Fig. 2.



Fig. 2 The seven main feelings. Rows one through three display photos from the JAFFE, FER, and CK+ databases, correspondingly

Most recent efforts in this area rely on the time-honored two-step machine learning procedure, which involves feature extraction from images as the first step and emotion detection using a classifier (e.g., random forest, SVM, or neural network). Results from unimodal systems are the basis of these works. Emotion prediction machines that rely solely on facial expressions [19] or vocal sounds [6, 20] no longer work.

Multimodal systems, which incorporate more than one factor into the emotion prediction process, eventually outperform single-feature systems. Thereafter, characteristics like audio-visual emotions, electroencephalogram (EEG), and body movements have been utilized in conjunction. Neural networks and other smart technologies power the emotion recognition system.

According to Shiqing et al. [21], multimodal recognition is superior to unimodal systems. Recent studies have shown that DNNs are capable of producing discriminative features that closely mimic the original set's

complicated non-linear dependencies [20]. Facial emotion detection often makes use of hand-crafted features for example; the histogram of oriented gradients (HOG) [22, 23], scale invariant feature transform (SIFT) [24], local binary patterns (LBP) and mapped LBP [25], Haar features [26] and Gabor wavelets [27].

The picture would then be given the most suitable emotion by a classifier. These algorithms performed admirably on simpler datasets, however, these shortcomings become obvious when dealing with more complicated datasets (exhibiting greater intra-class variation). In order to improve some defiance, we mention the problems of occlusion where the face can be occluded (eye-glasses, hat, hand or hair...) (Fig. 3).



Fig. 3 The face occlusion problem

The Table 1 presents the different popular datasets widely used for FER.

Table 1 The most relevant datasets of facial expression recognition

Name datasets	Database size	Description
Japanese female facial expression “JAFFE” (1998)	– There are a total of 213 photos in the database, featuring 10 Japanese female models posing for 7 different face expressions (1 neutral and 6 basic)	– On a scale from 1 to 6, 60 Japanese volunteers scored each image
Cohn-Kanade, CK (2000)	– Contains 100 university students	– Participants’ ages varied from eighteen to thirty. There were 65% females, 15% blacks, and 3% people of Asian or Latino descent
BU-3DFE Database (Static Data) (2006)	– Has one hundred participants and two thousand five hundred models of facial expressions expressions. The 100 participants’ ages range from 18 to 70 plus, with 56% being female and 44% being male	– Researchers can access the BU-3DFE database (e.g., computer vision, human computer interaction)

Name datasets	Database size	Description
The Bosphorus (2008)	– The 105 people in the 3D database are represented in a wide range of poses, expressions, and occlusion circumstances	– Most of the participants are in the 25–35 age range. In total, there are 45 ladies and 60 males
CK+ (2010)	– Contains 593 images in total from 123 subjects	– Participants ranged in age from 18 to 50, with 69% being female, 81% being Euro-American, 13% being Afro-American, and 6% belonging to other groups
BU-4DFE database (Dynamic Data) (2010)	– There are 43 male and 58 female participants in the final database. 606 sets of three-dimensional facial expressions from 101 people are included in the database	– A video the recording rate for here are 25 frames per second for the 3D facial expressions. There are six typical face expressions for every subject
The FER (2013)	– Contains 35,887 face images distributed across 28709 training sets, 3589 verification sets, and 589 test sets	– Each image is 48 pixels × 48 pixels in grayscale
CK+ (2024)	– Approximately 10.000 images and after augmentation between 50.000 and 100.000 images	– It emphasizes how crucial data augmentation methods are for enhancing model performance, especially when there is a shortage of labeled training data
CK+, FER2013 (2025)	– Approximately between 1.000 and 50.000 samples (images/videos)	– A deep learning framework that unites multimodal data fusion with CNN to enhance emotion recognition systems

In our study, we have chosen FER2013, JAFFE, and CK+ datasets, this selection on facial expression recognition (FER) is motivated by their complementary characteristics and widespread adoption in all researches. Using these datasets in combination affords a well-balanced evaluation framework encompassing data diversity, experimental control, and realism. This integrated approach enables thorough and reliable assessment of automatic facial expression recognition systems.

For studies including deep learning and vision, the “convolutional neural networks” (CNNs) topology has established as the gold standard. The top three competitors in the 2014 ImageNet object identification competition all used CNN methodologies; among them, the GoogLeNet architecture achieved an outstanding classification error rate of 6.66% [[27](#), [28](#)]. The GoogLeNet architecture employs an innovative multi-scale methodology by integrating many classifier architectures alongside different sources for backpropagation. Reducing back-propagation before

reaching the system's initial layers causes a number of issues, and this design solves those problems. Supplementary layers that diminish dimensionality enable GoogLeNet to expand in both breadth and depth without considerable drawbacks, thereby advancing towards the intricate network-in-network structures initially articulated by Lin et al. [29]. The design consists of several "Inception" layers, The design is able to conduct increasingly complex decisions because each node functions as a micro-network within the larger network [4].

Also, convolutional neural network (CNN) designs have shown remarkable results. The Convolutional CNN layered structure is the basis of AlexNet's architecture. The layers begin with convolutional layers, further on, the stack consists of rectified linear units (ReLUs), max-pooling layers, and numerous fully connected levels. The ILSVRC-2012 competition changed our view of CNN effectiveness with their leading error rate of 15.3%. This network was among the pioneers in using the "dropout" technique to address the overfitting issue, as proposed by Hinton et al. [30], which was essential in the advancement of massive neural networks. A significant problem in employing CNN designs that are commonly used are their computational complexity and depth. The complete network executes approximately 100 million operations per iteration, whereas Deep neural networks and SVM both utilize a lot less operations to develop an adequate model. This renders Convolutional CNNs challenging to implement in time-sensitive situations [4].

There have been outstanding outcomes with more conventional CNN designs as well. AlexNet [31] follows the traditional layered architecture of convolutional neural networks (CNNs), which starts with a large number of fully connected layers at the top and continues through max-pooling layers and rectified linear units (ReLUs) below. They completely changed our perspective on CNN effectiveness with has a top-five mistake rate of 15.3% at the ILSVRC-2012 event. Additionally, this network played a crucial role in the development of massive neural networks by being one of the first to use the "dropout" method, which was proposed by Hinton et al. [30] and was used to solve the overfitting problem. Traditional convolutional neural network (CNN) designs are notoriously difficult to implement due to their computational complexity and depth. When it comes to creating a good model, the entire network does something like 100 million operations in one iteration, whereas SVM and shallow neural networks do significantly

less operations. Because of this, using conventional CNNs in situations where time is of the essence is extremely challenging [4]. Essential information describing the geometric relationships of the face can be found in depth photos and films, which record the intensity of facial pixels as a function of distance from a depth camera.

For instance, in order to recognize face expressions, a CNN was used to unregistered facial depth pictures acquired from a Kinect depth sensor that had gradient direction information [32] retrieved a number of prominent Deep learning networks (such as CNN and DBN) were used in conjunction with characteristics extracted from depth films to perform facial emotion recognition (FER). When it comes to Li et al. [33] investigate the 4D Facial Expression Recognition (3D FER utilizing dynamic data) in order to draw attention to the changing patterns of distortion caused by changes in face expressions using a dynamic geometrical image network. Bypassing the need for facial landmark recognition, computing 3D expression coefficients from images intensities using CNN was proposed by Chang et al. [34]. As a result, the model is very resistant to severe appearance modifications, such as occlusions, size changes, and out-of-plane head rotations.

More and more research is looking at ways to improve performance by combining 2D and 3D data. Concurrent feature extraction from RGB and depth map latent modalities was achieved by Oyedotun et al. [35] using CNN. In order to study multi-modal 2D + 3D face emotion recognition (FER), Li et al. [36] implemented a deep fusion convolutional neural network (DF-CNN). To find the best weight combination for 2D and 3D face representations, as a first step, six distinct 2D attribute maps were derived from 3D face scans with textures: dimensions, texture, curvature, and the x, y, and z-axis normal components. These maps were then input into the networks that deal with fusing and extracting features.

Using texture and depth pictures to identify different facial regions [37], suggested extracting deep features and then merging them to create links through feedback. Using unsupervised domain adaption methods, Wei et al. [38] dug further into the 2D + 3D FER data bias problem [13]. Recently, Deep CNN (DCNN) is becoming the mainstream in face expression recognition there are several methods based on for FER, we adopt the (DCNN) architecture in our research, with review of some successful deep learning applications in FER. In Through the efforts of several researchers, we could obtain a good performance on these ideal datasets learning

methods, we have based on the researches of Shervin Minaee, Amirali Abdolrashidi in 2019 used the Deep learning methodology utilizing an attentional convolutional network with FER2013, CK, JAFEE, FERG datasets Achieved accuracy rate about: 70.02%, 98.0%, 92.8% and 99.3% respectively with different datasets [12].

Additionally, In 2020, Sahil Sharma and Vijay Kumar used sequential deep learning to apply voxel-based 3D face reconstruction to FER, they achieved accuracy rate about 90.01%, 78.21%, and 85.68% respectively with different datasets; Bosphorus, UMBDB, KinectFaceDB [39]. Recently, in February 2021, Nayaneesh Kumar Mishra and Satish Kumar Singh use the 3D CNNs for FER video datasets; CVBL, LFW, YTF achieved accuracy rate about: 97%, 99.42% and 95.0% respectively [40]. The significant accomplishment of deep learning, namely convolutional neural networks, pertains to image categorization and other visual problems [17, 41–45], Numerous groups established deep learning-based models for facial emotion recognition (FER).

The following table presents the different approach and successes of emotion recognition [4]. Those approaches perform important improvements compared to the previous approaches in emotion recognition, without attaining the problem of emotion detection respecting the important face regions (Table 2).

Table 2 Different approach and successes of emotion recognition [4, 12, 20, 40, 46–49]

Type of method	Reference and year	Approach and method	Data sets	Performance
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Type of method	Reference and year	Approach and method	Data sets	Performance
Handcrafted features methods	– Hu et al. (2019) [46]	– Fusion features for center-symmetric local signal magnitude pattern-based face expression recognition	– JAFFE, CK+	– Accuracy rate f 80 and 97.67% with the two datasets respectively
	– He and Chen (2020) [48]	– Higher-order singular-value decomposition and improved local binary pattern underpin person-independent face expression recognition	– CK+, Oulu-CASIA NIR&VIS	– The best average accuracy obtained are 82%, 77.5% respectively with different datasets
Deep learning methods	– Khorrami et al. (2015) [50]	– Master the use of facial action units in CNN-based expression recognition	– Cohn-Kanade dataset (CK+). Toronto Face Dataset (TFD)	– High accuracy in emotionrecognition, zero-bias CNN
	– Mollahosseini et al. (2016) [4]	– Deep neural network facial expression recognition	– MultiPIE, MMI, CK+, DISFA, FERA, SFEW, and FER2013 datasets	– More effective and faster to train than conventional convolutional neural networks

Type of method	Reference and year	Approach and method	Data sets	Performance
Deep learning methods	– Meng et al. (2017) [51]	– A convolutional neural network for facial expression recognition with identity awareness (IACNN)	– CK+ and MMI datasets	– Achieved accuracy rate about: 71.29%, 55.41% compared with the two datasets respectively
	– Shima and Omori (2018) [52]	– Image augmentation for classifying facial expression images by using deep neural network pretrained with object image database	– ATR facial expression image database (DB99)	– Average recognition rate of 97.92%
	– Minaee et al. (2019) [12]	– A method for deep learning that utilizes attentional convolutional networks	– FER2013, CK, JAFEE, FERG	– Achieved accuracy rate about: 70.02%, 98.0%, 92.8% and 99.3% respectively with different datasets
	– Sharma and Kumar (2020) [47]	– Using sequential deep learning, voxel-based 3D face reconstruction can be applied to facial expression recognition (FER)	– Bosphorus, UMBDB, KinectFaceDB	– Achieved accuracy rate about 90.01%, 78.21%, and 85.68% respectively with different datasets
	– Sharma and Kumar (2021) [49]	– 3D landmark based face restoration for recognition utilizing variational autoencoder and triplet loss	– Bosphorus, UMBDB, KinectFaceDB	– Achieved accuracy rate 83.3%, 77.2% and 80.9% respectively with different datasets

Type of method	Reference and year	Approach and method	Data sets	Performance
Deep learning methods	– Mishra and Singh (2021) [40]	– 3D FER using 3D CNNs using video data	– CVBL, LFW, YTF	– Achieved accuracy rate about: 97%, 99.42% and 95.0% respectively with video datasets
	Ezerceli and Eskil (2022) [53]	– For the FER-2013 dataset, a system based on convolutional neural network (CNN) algorithm for facial emotion recognition (FER)	– The combination of FER2013 and CK+ datasets	– Achieved 93.7% accuracy rate
	Bapat et al. (2023) [54]	– Building databases and using deep learning for facial expression recognition	– CK+ and FER2013	Attained 93.94% accuracy for the CK+ dataset and 67.18% for the FER2013 dataset, respectively
	Grover and Bansal (2024) [55]	– A lightweight convolutional neural network approach for efficient facial expression recognition on public datasets	– FER-2013, CK+, RAF-DB, KDFE	– Achieved 70, 99.2, 84.4, and 94% for, FER2013, CK+, RAF-DB and KDFE datasets respectively
	Chindiyababy et al. (2025) [56]	– Advanced human-computer interaction using deep learning-based facial emotion recognition	– FER2013, AffectNet, and CK+ dataset	– Achieved 92.5% accuracy rate for emotion recognition

3 The Proposed Model Architecture

3.1 Overview [57]

We had to do some digging to figure out what was going on and how to improve our results after the jobs were operational. Here, we'll break down the FER system into its component parts; Fig. 4 shows our proposed system.

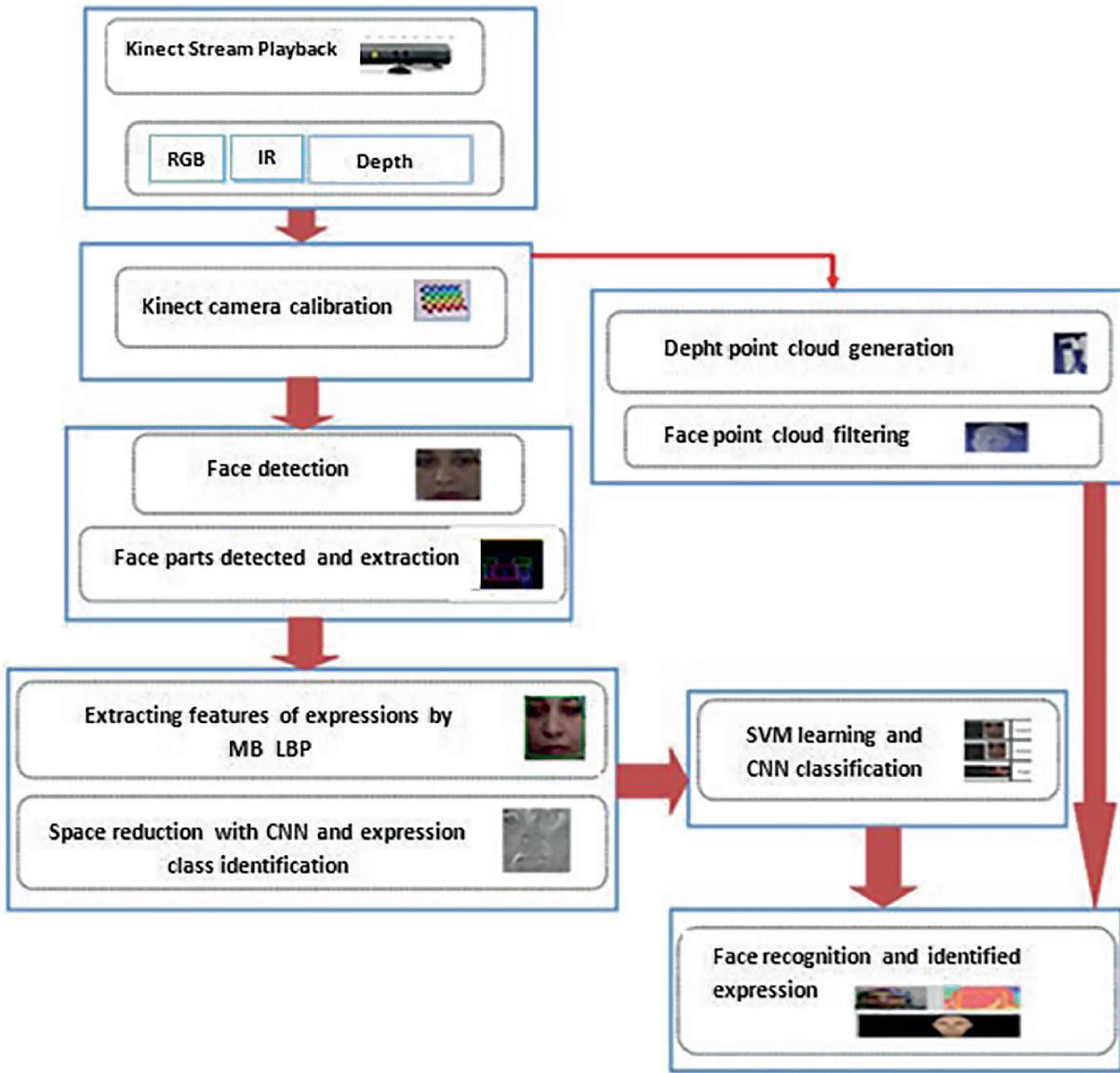


Fig. 4 Outline of our proposed approach [58]

The following encapsulates our overarching methodology.

3.1.1 Construct Dataset

We gathered labeled facial expression datasets from various sources and standardized their labels and photos into a uniform format. Subsequently, we incorporated personalized photographs of ourselves and a companion to enhance the data collection. In this study, we register facial images throughout each database utilizing established research methodologies. To ascertain the expression of the individual before the Kinect, we initially evaluated the image database. The “Viola-Jones” approach was introduced

for detecting faces in digital images or video sequences, and a “Haar Cascade Detector” implementation of this method is available in the OpenCV package. We decided to establish our own repository of expressions to circumvent the limitations of classification amid interclass variability linked to significant fluctuations in light within the same category. Finally, the program uses machine learning techniques to try to group the given face picture into seven different basic emotion groups. Support Vector Machines (SVMs) are predominantly employed for facial expression recognition applications. Based on our findings, facial registration improved the FER algorithms’ accuracy by 37%, implying that, registration is a crucial component of every FER method, much like normalization in conventional issues [4].

- **Pre-process Images:** In order to reduce the impact of poor data quality on the network, preprocessing is carried out. A point cloud representing information pertaining to the surface of a three-dimensional face coordinates (x, y, z) is the input to our suggested network. At first, we sub-sample points uniformly on 3D facial surfaces to remove the off-face area and bring the partial point clouds’ dimensionality reduced to N points per sample. We standardize the data on a scale from 0 to 1 so we can make a consistent point cloud [59].
- **Augmentation** [59]: We utilized facial-detection algorithms to isolate the face in each photograph. Subsequently, we re-scaled the cropping and manually removed substandard photos as a preliminary procedure for the CNN. The Using more training data can improve the neural network's effectiveness. One well-established way to improve a network's generalizability is to use data augmentation procedures. Data augmentation involves generating additional samples for each class through various transformations while maintaining exactly the same amount of courses. Its purpose is to avoid overfitting and improve training robustness:
 - On the vertical axis, the three-dimensional face is tilted at 90°.
 - To improve the data, a small amount of random point rotation is applied ($\sigma = 0.06$ and $\text{angle-clip} = 0.18$).
 - Using 0.02 as the mean and 0.06 as the standard deviation for the Gaussian noise to disturb the location of each point cloud.

- Performing all of the aforementioned methods for enhancing data at the level of the point cloud, including rearranging the sequence of points within each cloud and applying random translations and scaling to the data within the clouds.
- Rearranging the sequence in each point cloud, using a combination of the aforementioned data augmentation approaches applied to the point cloud data through random translations and scaling.

3.1.2 Feature Extraction

Is an important step because it determine the result we use one of most popular for face analysis MB_LBP which use the texture feature that is robust to misalignment and the variation of illumination. LBP original can be considered like a particular case of MB_LBP [58, 60], we require a Support Vector Machine (SVM) classifier to categorize the extracted characteristics [61, 62]. The Fig. 5 showed an example of image and its different intensities.

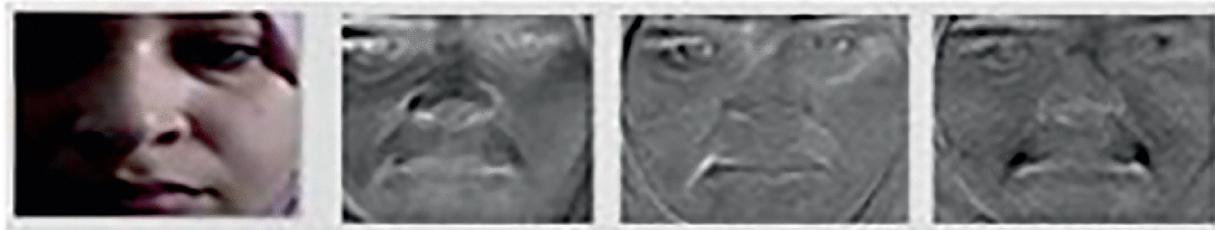


Fig. 5 Example of image and its different intensities [58]

- **Feature\Pooling dimension reduction;** Construct CNN: The objective of CNN design is to resize the image to a format that can be efficiently processed without sacrificing essential features to get accurate predictions [61]. The CNN method operates by transmitting the input image via a series stacked layers, which include the fully connected layer, pooling layer, rectified linear unit, and convolution layer, to yield an accurate result. The CNN methodology incorporates an integrated classifier known as Soft Max for picture classification.

The objective of CNN was to convert the input set into accurate and valid outcomes [61]. Resilient to variations in location and scale invariance in facial expression recognition, CNN comprises five layers: convolutional layers (used to diminish the spatial dimensions of the features), pooling

layers, and fully connected layers. Average pooling and max pooling are the two most prevalent nonlinear down sampling techniques employed for achieving translation invariance [13]. We employed pre-trained variants of AlexNet, re-training the initial and final layers. We needed to explore several learning rate techniques and parameters to produce a non-divergent model.

3.1.3 Create an Interactive User Interface

OpenCV enabled us to acquire images from our trials; we utilized Microsoft Kinect for 3D facial modeling mostly due to its affordability and ease of use. The Kinect possesses a limited scanning resolution, although it maintains a comparatively high image registration rate of 30 frames per second. It is equipped with an infrared emitter and dual cameras. One camera captures visible light, while the other functions in the infrared spectrum and is utilized for depth measurement [63]. Infrared photons reflected from the user's body facilitate the creation of a 3D facial model. The model (Candid3 [64]) is founded on 121 distinct facial points, captured by the Kinect gadget. These points are positioned at distinctive locations on the face, including the corners of the mouth, cheekbones, nose and eyebrows. Figure 6 illustrates a collection of distinctive facial points recorded in 2D space (a) and the coordinate system (x , y , z) as delineated by the Kinect device (b). Subsequently, we isolated the face as previously, pre-processed the image for the CNN, and transmitted it to AWS. A script on the server would process the image through the CNN, obtain a prediction, and retrieve the results locally [1].

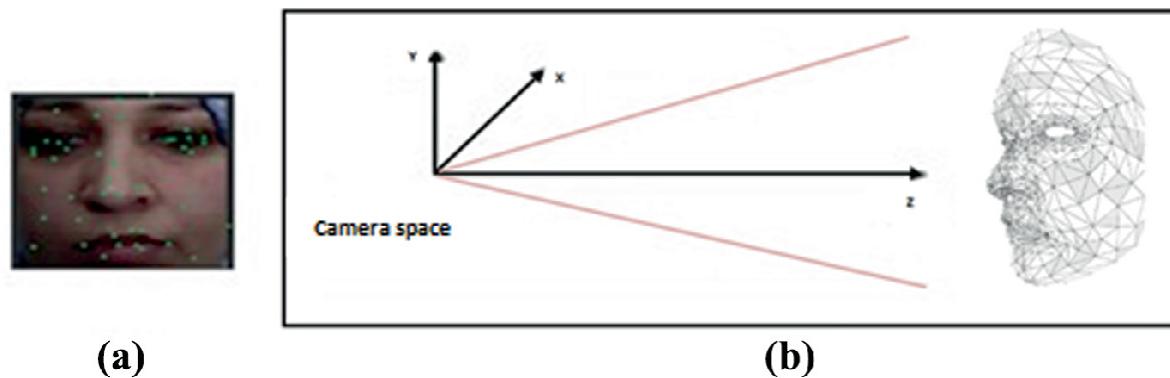


Fig. 6 a Feature points on the face, b kinect coordinate system

3.2 CNN Construction [4]

The advancement of neural network architectures relies on optimizing either the amount of neurons or layers, allowing the network to learn intricate functions. But problems like rising CPU requirements and training data overfitting become more apparent as topologies become deeper and more complicated.

Building deep sparse networks with strong theoretical foundations and biological inspiration is the easy way to tackle the problem of dense networks, as described by Arora et al. [65]. Actually, computing processes over infrequent networks are beyond the capabilities of modern GPUs and CPUs. By assessing sparse networks that take use of the advantages stated in theory by Arora et al., with the dense architecture necessary for effective computation preserved [4], the first layer offered in [63] resolves these issues. Several convolutional neural network (CNN) models were cited: AlexNet (2012), GoogleNet (2014), VGGNet (2014) and ResNet (2015).

As shown in [66, 67], the Inception layer has shown outstanding results when used to Deep Neural Network applications. Consequently, it makes sense to apply the sophisticated methods used for object recognition to the problem of facial expression recognition (FER). In addition to the theoretical benefits of a sparse and relatively deep network, the first layer uses smaller convolutions to improve local feature recognition and larger convolutions to approximatively represent global features. There seems to be a reasonable correspondence between the way people express their feelings and the improved local performance. Most facial expressions, especially those involving the eyes and lips, are easily identifiable to humans [27].

Without guidance to concentrate on certain regional characteristics, children with autism may have difficulty correctly identifying emotions. Our expectation is that there will be notable improvements in local feature performance, which should lead to better FER results, while applying Lin et al.'s [68] network-in-network theory [68] and use the first layer structure. The network-in-network approach has many benefits, one of which is a decreased vulnerability to overfitting thanks to improved local and global pooling performance. Because the network is resistant to overfitting, we can increase its depth without worrying about the small image dataset we have for the FER task. Section 3.2.3 lays out the principles of AlexNet topologies that informed the research presented in this paper.

- Our network comprises two components: it includes two Convolutional CNN modules, each one including a max pooling layer after a convolutional one. The activation function of a rectified linear unit (ReLU) is $f(x) = \max(0, x)$, where x is the input to a neuron, and both modules use this function. The vanishing gradient problem is mitigated when using the ReLU activation function in conjunction with alternate activation functions (for more information, see [29]).

3.2.1 Application of Deep Convolutional Neural Networks for Classification

Classification and grouping of images based on similarities is the primary use of artificial neural networks that use convolutional neural networks as their basis. A method with many potential uses is the convolutional neural network (CNN), including character recognition, anatomy, tumor detection, street sign recognition, and many more. Discrete Convolutional Neural Networks Emotion detection using visual analysis is fundamentally a challenge with picture categorization. So, it stands to reason that a top-tier DCNN model with strong picture classification capabilities would also demonstrate strong face expression recognition capabilities. The initial ConvL C1 uses a 5×5 convolution kernel, however it is 3×3 for the C2 and C3 foundation layers. The reason for the difference is that the size of the convolution kernel for the latter two convolutions is 3×3 , which leads to better results. This is because using two 3×3 enhances the network's capacity for non-linear operations, leading to a more discriminative decision function. However, if the initial 3×3 layer is used, underperforming because the parameters of the network model are undersized. The layer's mathematical expression is given by [39]:

$$x_i^l = f \sum_{i \in M_j^{l-1}} x_i^{l-1} K_{ij}^l - 1 K_{ijl} + b_j^l \quad (1)$$

According to [39], the variables l , f , k , b , and M_j stand for the layer, activation function, convolution kernel, bias, and feature map, respectively.

We experimented with many DCNN models, including customized iterations of AlexNet, VGG, GoogLeNet, and ResNet. This research is not aim to compare other DCNN models; hence, we utilize a proprietary

AlexNet network to illustrate emotion identification efficacy on the FER dataset [69]. Discrete wavelet transform was used to extract features of the human face's local texture. The deep convolutional neural network takes the output as its input. This research proposes a network architecture with three convolutional layers, two pooling layers, and one fully connected layer, as illustrated in Fig. 7 [39].

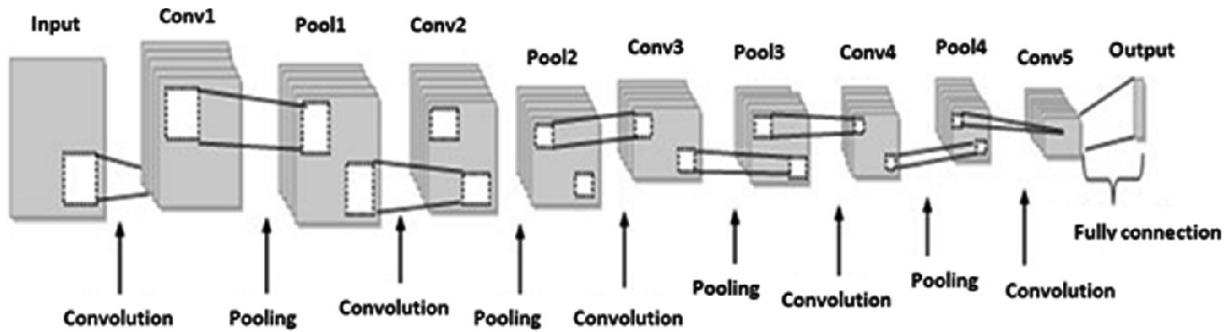


Fig. 7 La structure convolution network proposée

3.2.2 Max Pooling

Max pooling addresses two issues for convolutional neural networks (CNNs); it reduces dimensionality by reducing each layer's output size and the resources available to the network with translational invariance. The latter is significant because if a feature is displaced marginally by a few pixels, it will be aggregated in a “max pool” and subsequently sent to later layers of a broader framework. This has demonstrated superior performance compared to other pooling strategies, such as average pooling. Figure 8 illustrates an example of this process [70].

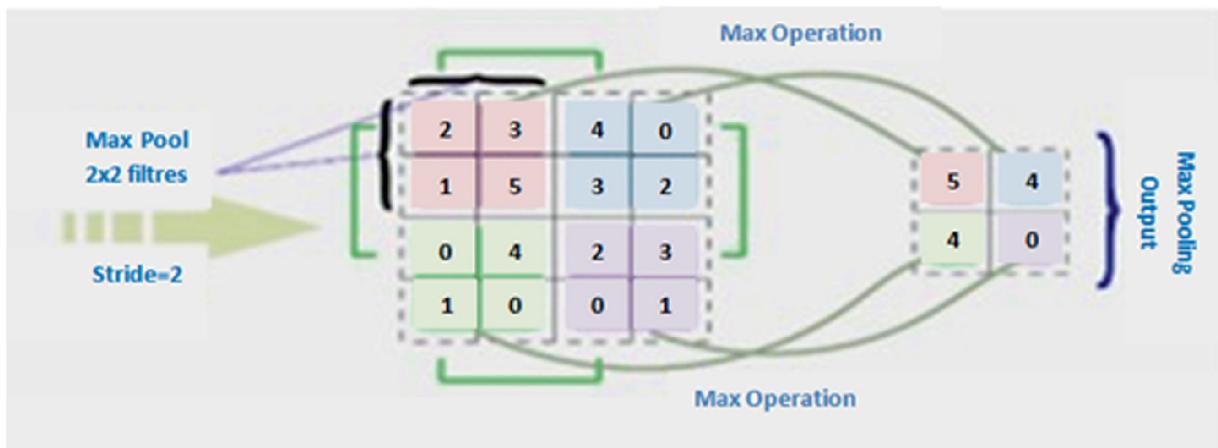


Fig. 8 Technique of maxpooling [70]

3.2.3 AlexNet

This is the shallowest network we trained and tested, consisting of only 5 layers. The complete architecture and adaptation are illustrated in Fig. 9. The Feature Selection Network (FSN) integrates a feature selection mechanism within AlexNet, which autonomously eliminates irrelevant features and highlights linked features based on learnt feature maps of facial expressions [13].

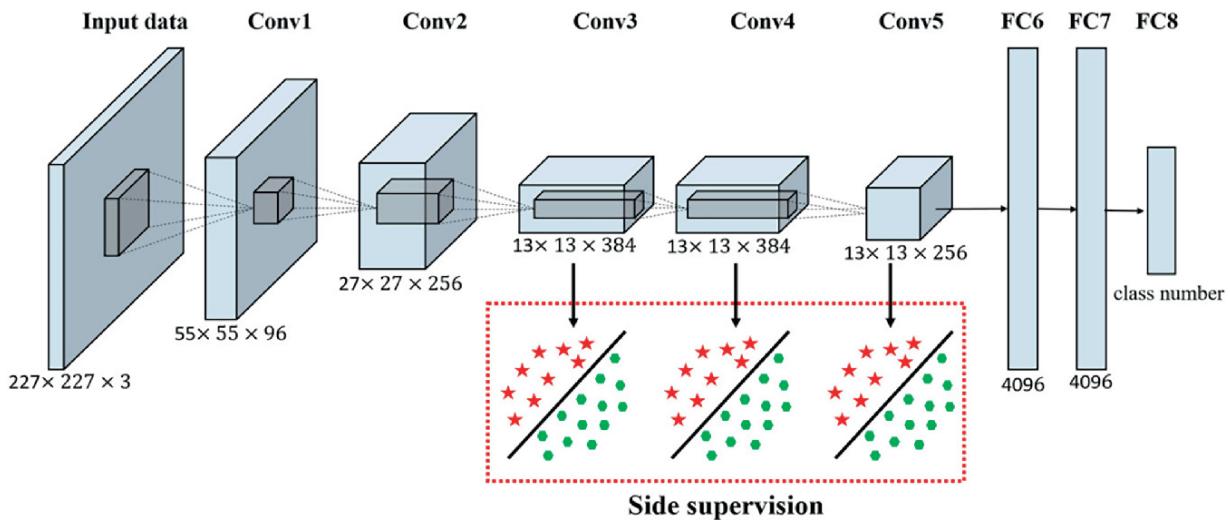


Fig. 9 AlexNet architecture [13]

After these modules, we build the network using its techniques and include two “Inception” type modules with convolution layers that are 1×1 , 3×3 , and 5×5 , all of which are connected using ReLU. To combine two completely linked layers, the layers as output used for classification via ReLU activation. The study's network architecture is shown in Fig. 10.

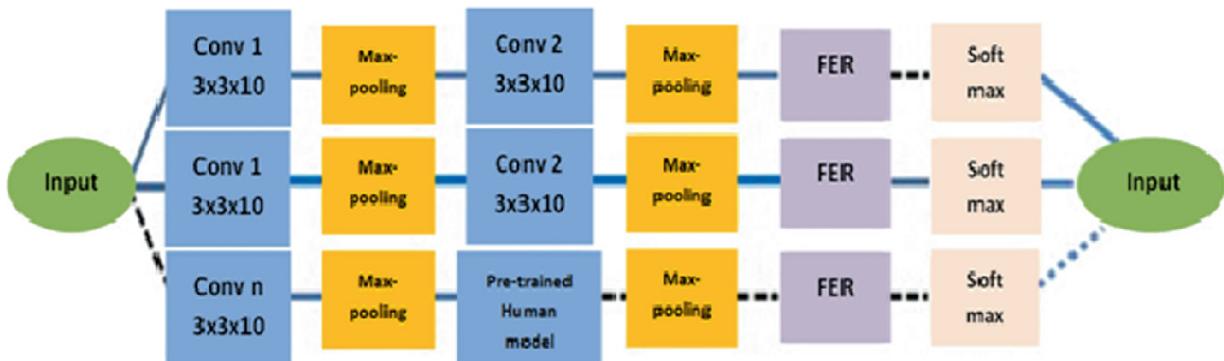


Fig. 10 Overview of CNN design. Fully linked expression recognition layers, max pooling layers, and the convolutional layers (Conv) are identified by $n = 5$ layers, with each layer labeled

accordingly

3.2.4 Classification Expression

In the last step, the deep network performs facial emotion recognition (FER) to assign each given face a fundamental emotion. To reduce the dispersion of the expected class probabilities throughout the distribution of the ground truth, CNNs mainly employ the Softmax loss function. Further, another method calls for separate classifiers to be applied once deep neural networks have been used to extract features [13]. Using the softmax regression classifier, as described in this work, the classifier layer functions as the CNN's output layer. Using the data x as input for a particular training session, the softmax function acts as a multi-class classifier in the network's final layer, boasting robust non-linear classification capabilities. The set $\{1, 2, \dots, k\}$ includes the output category y , which means there are a total of k classes; for the purposes of this article, we will define k as 10. The following is the probability distribution of the class $y = i$ that it belongs to, assuming that the input data x is defined: In equation [71], for instance, “ i ” denotes the parameters that require estimation, “ e ” is the base of the natural logarithm, and “ t ” denotes the transposition. “What is the meaning of:”

$$P(y = i|x ; \Theta) \quad (2)$$

The input data x 's chance of belonging to each class i takes on values between 1 and k [39].

$$P\left(C_j = \frac{1}{x}\right) = \frac{e^{w_{jx}^t}}{\sum_{i=1}^k e^{w_{ix}^t}} \quad (3)$$

4 Experimental Results

Extensive experimental testing of tested our model on various databases for facial expression recognition is presented in this part. We begin with a brief summary of the databases used in this research; next, here, we describe in detail how well our models performed across three databases, comparing the results to those of other renowned prior research. We subsequently

present the prominent locations identified by the use of a visualization method by our trained model.

4.1 Face Databases

A number of notable, freely accessible databases of facial expressions are used to evaluate the proposed methodology. These databases include JAFFE, CK+, and the Facial Expression Research Group Database (FER2013) [11].

- **JAFFE:** Ten Japanese female models display seven different facial expressions in this dataset's 213 photos. Sixty Japanese volunteers rated each image using six emotional adjectives [10] (see Fig. 2 the images in the first).
- **CK+:** Each of the 593 images in this collection—taken by 123 different individuals—depicts a human face expression that the subject has assigned to one of the seven basic emotions. From 18 to 50 years old, 69% of the participants are female, 81% are of Euro-American descent, 13% are of Afro-American descent, and 6% are of some other ethnic group. Pixel arrays ranging from 640×490 to 640×480 were created from image sequences that were intended for frontal and 30° viewpoints. You can see the database in action in Fig. 11 [72, 73].

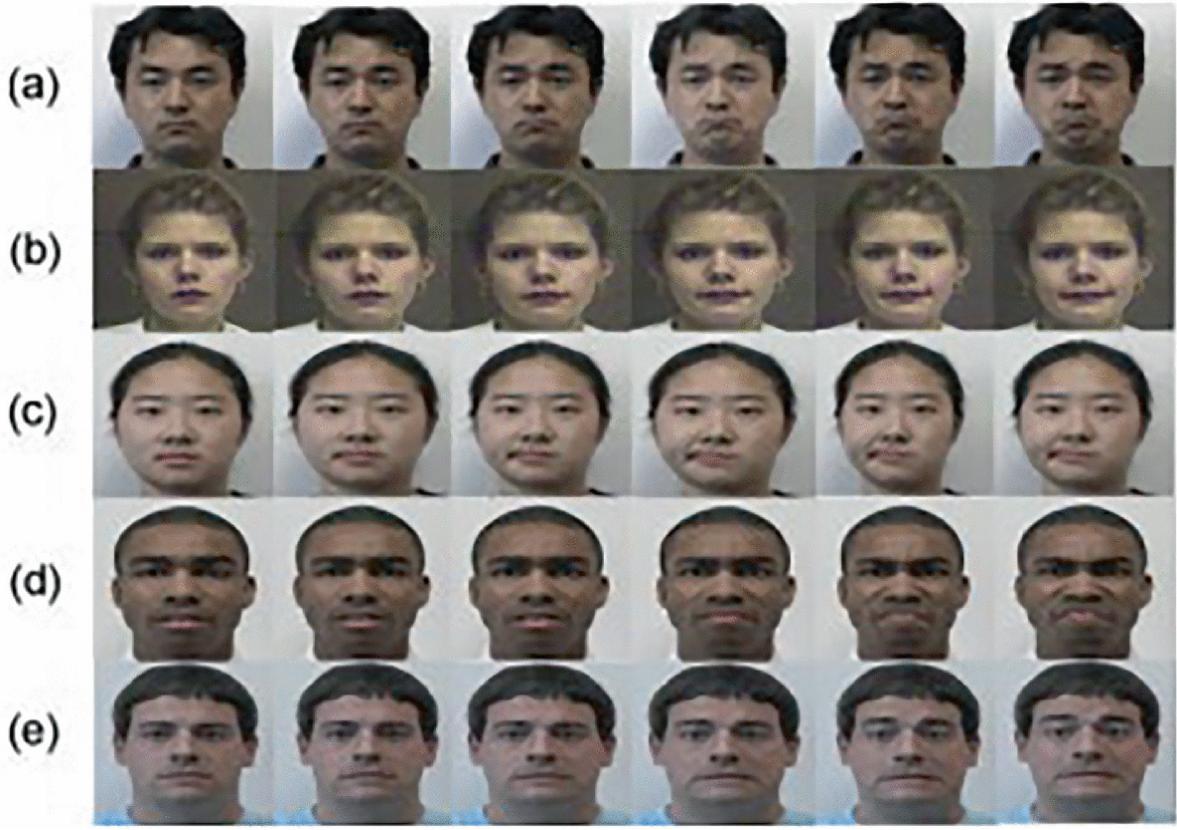


Fig. 11 Examples among CK+ dataset [73]

- **FER2013 Face Dataset:** The FER dataset is specifically given for a Kaggle competition. The dataset comprises 35,887 facial images, consisting of 28,709 training samples, 3,589 verification samples, and 589 test samples, all of which are grayscale images measuring 48 pixels by 48 pixels. The samples are categorized into seven groups based on a generally uniform distribution: furious, unpleasant, terrified, pleased, neutral, sad, and amazed. Each sample in the collection exhibits significant variability in age, facial orientation, and other characteristics, closely resembling real-world conditions [11, 74] (Fig. 12).



Fig. 12 FER2013 face dataset [11]

The following table summarizes our experimental results on the datasets already mentioned with the seven standard expressions (Table 3).

Table 3 Our experimental results using the datasets “JAFFE, FER2013, CK+”

Dataset	Dataset size	Number of training images	Testing images	Accuracy (%)
JAFFE	213 images	163	24	98.86
FER2013	35,887 images	28,709	15,11	93.76
CK+	593 images	732	347	97.88

4.2 Comparison and Analysis of Experiments

Using the aforementioned datasets, we will now show that the proposed deep neural network architecture is effective. Each case involves using a subset of the dataset for model training, a separate set for validation, and a test set for accuracy reporting. There is complete object-agnostic categorization of databases into test, validation, and training sets. To evaluate the results, K-fold cross-validation, with $K = 5$, was employed. When it comes to JAFFE and CK+, in the release of the database, the training and test sets are specified. Instead of employing K-fold cross-validation, the results are evaluated on the selected test set. The training, validation, and test sets show small differences in sample sizes across each fold because different databases have different sample sizes per mood and participant.

Approximately 21,315 photos (or about 70% of the total) are used for training, whereas 1,530 images (or about 30% of the total) are used for

testing. Two thousand images are chosen at random for the purpose of assessing each facial emotion. We achieved a precision level of around 93.76%.

The comparison between the proposed technique and other prior research on the FER2013 dataset is presented in the Table 4.

Table 4 Demonstrates the efficacy of our suggested algorithm in comparison to alternative methodologies on FER2013 dataset

Approach	Average accuracy percentage (%)
CNN (2023) [54]	67.18
Lightweight CNN (2024) [55]	70
Multimodal data fusion with CNN (2025) [56]	92.5
The proposed algorithm	93.76

In the JAFFE dataset, we employed 138 photos for training, accounting for roughly 70% of the total, and 53 test photos, or 30% of the total. The complete accuracy of this dataset is approximately 98.86%. Table 5 presents a comparison between the proposed technique and several precedent researches on the JAFFE dataset.

Table 5 Demonstrates the efficacy of our proposed algorithm in comparison to alternative methodologies utilizing the JAFFE dataset

Approach	Average accuracy percentage (%)
Fusion-CNN (2023) [75]	93.07
CNN + SVM(2024) [76]	89.23
Deep CNN (2025) [77]	98.12
The proposed algorithm	98.86

In the CK+ dataset, we employ 380 photos for training, comprising approximately 70% of the total comprises 163 images designated for testing, or roughly 30% of the whole dataset. The total correctness of this dataset is approximately 97.88%. Table 6 presents a comparison between the proposed approach and several preceding efforts on the CK+ dataset.

Table 6 Demonstrates the efficacy of our suggested algorithm in comparison to alternative methodologies on the CK+ dataset

Approach	Average accuracy percentage (%)
Fusion-CNN (2023) [75]	98.22
CNN + SVM (2024) [76]	96.19
Deep CNN (2025) [77]	99.3
The proposed algorithm	97.88

We note that with the three datasets proposed our performance, producing satisfactory outcomes, with an average accuracy rate of approximately 96.83% in comparison to the other datasets.

4.3 Evaluation of AlexNet on the Test Set

Upon training AlexNet, we attained the subsequent accuracies across all categories (Fig. 13).

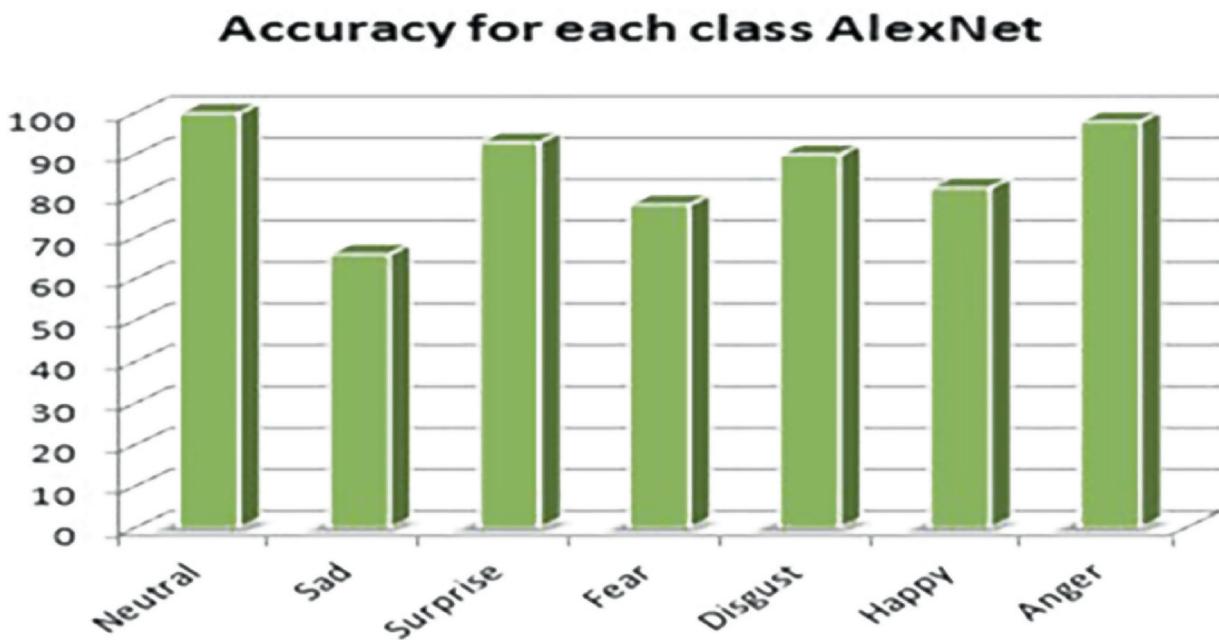


Fig. 13 Accuracies across all classes AlexNet

Overall, our network achieved an average accuracy of 87% across all categories, with the highest accuracy in the neutral category and the lowest in the sad category.

5 Conclusion

Using a convolutional network built on the AlexNet architecture, this study introduces a new framework for deep neural networks that can automatically identify facial expressions in real-time. Each of the five convolutional layers in the suggested network is followed by max pooling, and then there are five fully linked layers. Extensive experimental testing on the three most popular facial expression recognition databases, namely JAFEE, FER2013, and CK+, revealed encouraging outcomes. The results show that our network is better than existing state-of-the-art methods, which usually maximize the organized features and classifier parameters on the datasets. By minimizing operational requirements for network training and improving classification accuracy in subject-specific and cross-database evaluation settings, the proposed method outperforms existing CNN algorithms.

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Feature Aggregation for Efficient Continual Learning of Complex Facial Expressions

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Abstract

As artificial intelligence (AI) systems become increasingly embedded in our daily life, the ability to recognize and adapt to human emotions is essential for effective human–computer interaction. Facial expression recognition (FER) provides a primary channel for inferring affective states, but the dynamic and culturally nuanced nature of emotions requires models that can learn continuously without forgetting prior knowledge. In this work, we propose a hybrid framework for FER in a continual learning setting that mitigates catastrophic forgetting. Our approach integrates two complementary modalities: deep convolutional features and facial Action Units (AUs) derived from the Facial Action Coding System (FACS). The combined representation is modelled through Bayesian Gaussian Mixture Models (BGMMs), which provide a lightweight, probabilistic solution that avoids retraining while offering strong discriminative power. Using the Compound Facial Expression of Emotion (CFEE) dataset, we show that our model can first learn basic expressions and then progressively recognize compound expressions. Experiments demonstrate improved accuracy, stronger knowledge retention, and reduced forgetting. This framework contributes to the development of emotionally intelligent AI systems with applications in education, healthcare, and adaptive user interfaces.

Keywords Facial expression recognition – Continual learning – Feature fusion – Action units – Probabilistic models

1 Introduction

Advances in Artificial Intelligence (AI) have made intelligent systems an integral part of our daily lives. With increasing integration into our technological environment, the ability of AI to assess and distinguish between different emotional states has become essential for improving human–computer interaction [1, 2]. Facial Expression Recognition (FER) provides a channel to infer, analyze, and study how individuals express their emotional states through facial expressions.

The most common categorization of emotions is Ekman’s basic emotions [3], which consist of six basic categories: anger, fear, disgust, happiness, sadness, and surprise (see Fig. 1), along with the neutral state representing the absence of emotion. This representation has become a baseline for emotion analysis. Its simplicity and universality have enabled the creation of numerous datasets in the FER context, and most FER algorithms rely on Ekman’s annotation as a basis for classification. While this categorization is useful, in real-life contexts it can be limiting due to the complexity and subtlety of emotions. For this reason, other annotation systems were developed to analyze emotions in specific contexts such as learning. For example, Arthur Graesser and Sidney D’Mello [4] used a set of annotations for emotions occurring during the learning of difficult material. Such context-specific annotations can be very useful to study emotional states in activities like learning, job interviews, or clinical settings. However, creating datasets for such subtle expressions is both complex and time-consuming, which also complicates the development of FER systems for their classification. An alternative approach is to study compound expressions (Fig. 2) which represent facial expressions formed by the combination of two or more basic emotions. These expressions are not represented by simple combined activations of the facial muscles from the separate expressions but are considered distinct and recognizable affective states which allow us to move beyond the basic expressions and study more nuanced and complex expressions which are more representative of real-life interactions.

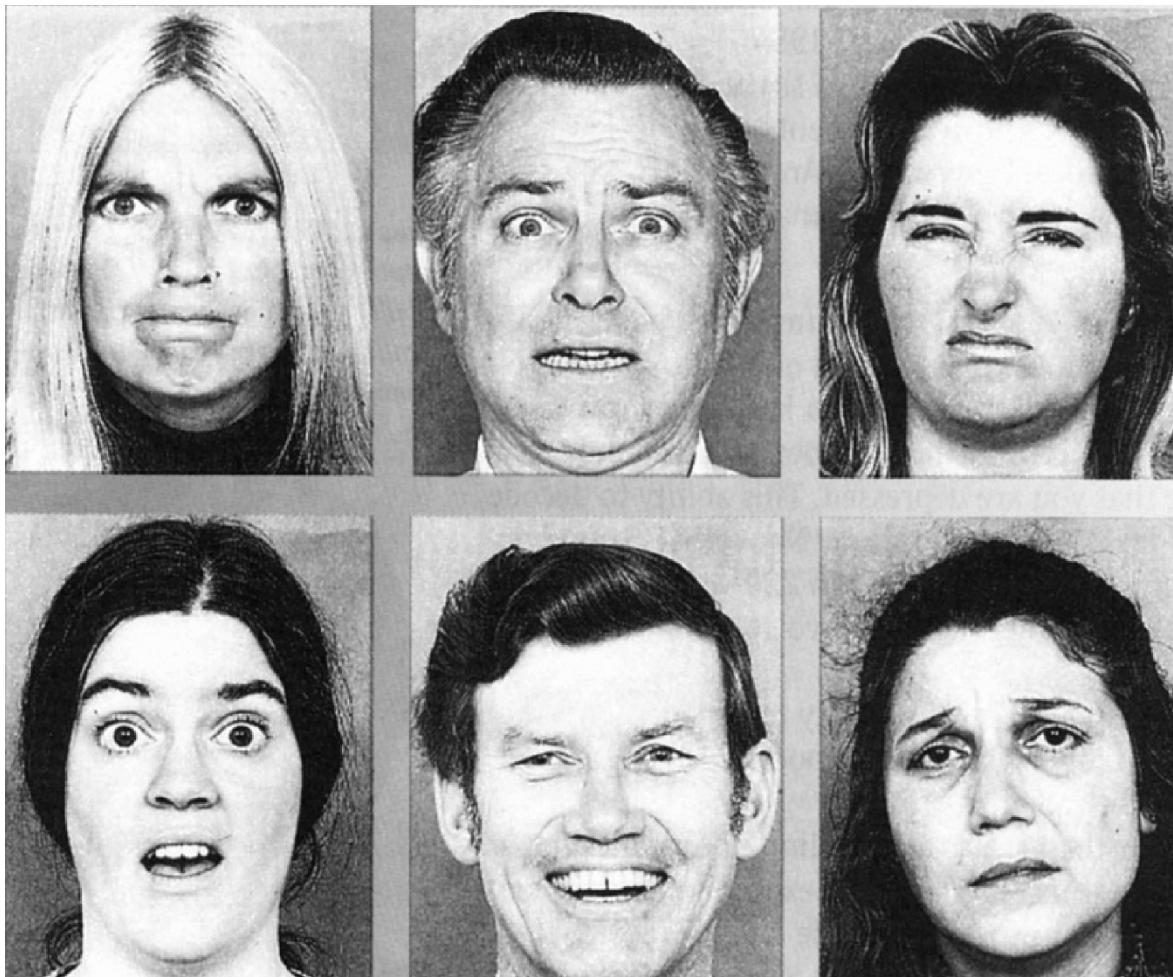


Fig. 1 Ekman's 6 emotional expressions [5]



Fig. 2 Compound facial expressions [6]

In addition to end-to-end systems such as Convolutional Neural Networks (CNNs), which learn features jointly with expression classification, other methods can be used to extract features for FER. Facial Action Units (AUs), introduced by Ekman and Friesen [7], categorize facial muscle activations, and provide a structured and objective representation of facial expressions. Integrating multiple feature types for classification has already proven effective [8], particularly in scenarios with limited training data, where continual learning is especially challenging. Although CNN-extracted features are powerful for the tasks they are trained on, their generalization is reduced on unseen tasks, and continual training of CNNs can increase catastrophic forgetting [9].

Continual learning is a machine learning paradigm that enables models to learn continuously during deployment. In this setting, data become available sequentially, either one instance at a time or in batches, and the model is trained with little or no access to previous data. Without appropriate strategies, this leads to significant knowledge loss on previously learned tasks, a phenomenon known as catastrophic forgetting. This issue is one of the main challenges in continual learning and has been extensively studied [9–11]. The objective of continual learning is to acquire new information while retaining old knowledge. Some methods address this by storing parts of the dataset, but this increases memory requirements and raises privacy concerns. For this reason, example-free methods are increasingly studied [12, 13].

Many applications of continual learning involve learning new classes of objects. Datasets such as CIFAR-100 [14] and ImageNet [15] are benchmarks for such tasks, where the model must recognize very different objects, ranging from apples to cars or even porcupines. These diverse recognition tasks impose high complexity, as the model must make accurate predictions without suffering catastrophic forgetting. In the FER context, however, continual learning tasks are not completely disjoint: all data consist of faces, and the goal is to detect and classify new emotional expressions. For example, the Compound Facial Expressions of Emotion (CFEE) dataset [6] contains both Ekman’s basic emotions and compound expressions. These compound expressions are distinct and culturally consistent facial patterns formed by the combination of two or more basic emotions, such as “happily surprised” or “sadly fearful.”

Several approaches have been proposed for such tasks, including regularization, and retraining of the model, but they perform poorly in this context. Moreover, since compound expressions are less frequent, the available labeled data are much more limited than for basic expressions, making neural network retraining difficult.

Since Action Units alone are not sufficient to classify compound expressions, and continuously retraining CNN feature extractors leads to catastrophic forgetting, our approach combines low-level features from a pre-trained CNN [16] with high-level features derived from Action Units. This hybrid representation enhances accuracy in compound expression recognition.

For the inference itself, most state-of-the-art FER approaches rely on deep neural networks, but these models are not always appropriate for continual learning. Probabilistic models offer several advantages: their ability to model class-conditional

distributions allows class-by-class analysis and reduces vulnerability to catastrophic forgetting. Gaussian Mixture Models (GMMs) have shown strong performance in modeling data distributions, as FER classes often form clusters in the feature space. However, classical GMMs require fixing the number of mixture components in advance, which is a costly hyperparameter to optimize. To address this limitation, we employ Bayesian Gaussian Mixture Models (BGMMs), which automatically infer the optimal number of mixture components. This enables the model to adapt its complexity to the data and represent class distributions more robustly.

Our approach combines multimodal feature vectors with Bayesian Gaussian Mixture Models to achieve strong performance in facial expression recognition within a continual learning framework.

The two main contributions of this work are:

- Demonstrating the utility of multimodal feature fusion for accurately classifying both basic and compound facial expressions.
- Introducing an efficient probabilistic model that enables continual learning with minimal training overhead while effectively mitigating catastrophic forgetting compared to CNN-based approaches.

1.1 Related Works

Facial Expression Recognition

Facial Expression Recognition (FER) is a pivotal domain in affective computing, aimed at automatically identifying human emotional expressions through facial cues. Traditional FER systems have historically relied on geometric or appearance-based features such as Active Shape Models (ASM) [17], Local Binary Patterns (LBP) [18], or Gabor filters [19]. Though robust, these methods struggle with generalization when applied to unconstrained data [20].

With the rise of deep learning, Convolutional Neural Networks (CNNs) [21] and their extensions such as Long Short-Term Memory (LSTM) models [22] have significantly boosted FER performance, especially on datasets such as CK + [23], FER2013 [24], or RAF-DB [25]. These models are often fine-tuned from pretrained image classification architectures (e.g., VGG, ResNet, EfficientNet) and consistently outperform classical methods by learning discriminative features in an end-to-end fashion [20].

However, these deep learning approaches are typically trained in classical setting where the whole set of training data arrives all at once and are prone to catastrophic forgetting when required to adapt to new distributions of data or new classes. This makes them not suitable for continual learning.

Continual Learning

Continual learning has emerged as a necessary framework for machine learning models that must adapt over time to new data distributions and classes without forgetting previously acquired knowledge. The field categorizes approaches into regularization-

based methods (EWC [9]), replay-based strategies (FearNet [26]), architecture-based expansions (ZOO [27]) representation-based (DualNet [28]) or optimization-based methods (GEM [13]).

Unlike generic object classification benchmarks such as CIFAR-100 or ImageNet [15], FER tasks involve overlapping domains (all tasks concern facial data) but shifting label semantics (e.g., from basic to compound expressions). This makes continual learning in FER a more structured and domain-specific challenge. The Compound Facial Expression of Emotion (CFEE) dataset, which includes both basic and compound expressions, is particularly well suited for investigating these dynamics thanks to its natural separation between simple and more complex emotions.

Yet, most continual learning methods are evaluated on object recognition datasets with clearly distinct tasks and classes. In contrast, FER involves different types of expressions derived from the same facial images, meaning that all tasks share a common basis of recognizing facial features. This strong similarity between tasks calls for approaches that can better exploit the inherent structure of FER data while remaining computationally efficient.

Generative and Probabilistic Models

Generative models such as GANs offer a solution to catastrophic forgetting by approximating past data distributions, enabling the virtual replay of old task data. However, these methods can be resource-intensive and remain prone to forgetting when continuously trained [29]. An alternative lies in probabilistic models, which explicitly model data distributions. By modeling each class distribution separately, they mitigate catastrophic forgetting by preventing interference between new and old classes.

Among these, Gaussian Mixture Models (GMMs) [30] and Bayesian Gaussian Mixture Models (BGMMs) [31] have demonstrated strong discriminative capabilities in FER [32]. In FER, where class distributions are naturally clustered yet sometimes highly overlapping (particularly for compound emotions), GMM-based approaches provide a lightweight and interpretable solution. Our work integrates BGMMs trained conditionally on each class within a multimodal representation space (combining CNN-extracted features and Action Units), enabling continual acquisition of knowledge on increasingly complex expressions while mitigating catastrophic forgetting.

Prior FER studies applying GMM or BGMM have mostly done so in classical settings and typically rely on a single feature modality, limiting their capabilities for complex tasks like recognizing compound expressions. Our work addresses these limitations by using BGMMs with several feature vectors extracted from the images combining CNN-extracted features and Action Units. This approach uses both low-level and high-level information, enabling more resilient continual learning and reducing catastrophic forgetting through the continual learning process.

2 Main Content

2.1 Method

2.1.1 Intuition

The main idea behind our model is the following: since we are working on a set of related tasks centered on facial image analysis, we chose to specialize the model within this specific domain rather than extend it to unrelated tasks. In this context, combining different types of features, with high-level features such as Action Units and low-level features extracted by a CNN-based encoder, enables the model to classify not only basic expressions but also more subtle ones, including compound expressions.

2.1.2 Architecture

Our model consists of three parts: an ensemble of feature extractors, a feature aggregator, and a probabilistic classifier. The feature extractors can be of different types (CNN-based features, Action Units, etc.) and are designed to compute complementary information, so that one can help compensate for the other's errors. In our implementation, we employ two feature extractors. The first is a CNN trained exclusively on basic emotions, from which we use the features extracted at the penultimate layer. The second is an Action Units extractor [33]. These two sources of information, one providing a low-level feature vector trained on the dataset and the other a high-level feature vector, together form a strong representation of the subject's face and emotional expression.

The second component of the model is a feature aggregator that combines the outputs of both extractors. In this initial experiment, the aggregation strategy is limited to a simple concatenation of the two feature vectors, namely those extracted from the CNN and the Action Units. This serves as a first step to evaluate the viability of the approach. Future work will explore more advanced aggregation strategies, such as weighted fusion or Principal Component Analysis (PCA), to construct a more robust and discriminative feature representation.

The final part of the model is a set of K Gaussian mixtures, where K corresponds to the number of classes. Each mixture contains one or more Gaussian distributions $G_k = (\mu_k, \Sigma_k)$. To determine the optimal number of components, we rely on the Bayesian Gaussian Mixture approach [31], which prunes redundant components during training [34]. Each conditional Gaussian mixture is initialized when its class appears and is trained to learn the conditional distribution of its class. Thus, each Gaussian mixture acts as an expert specialized in its own class (Fig. 3).

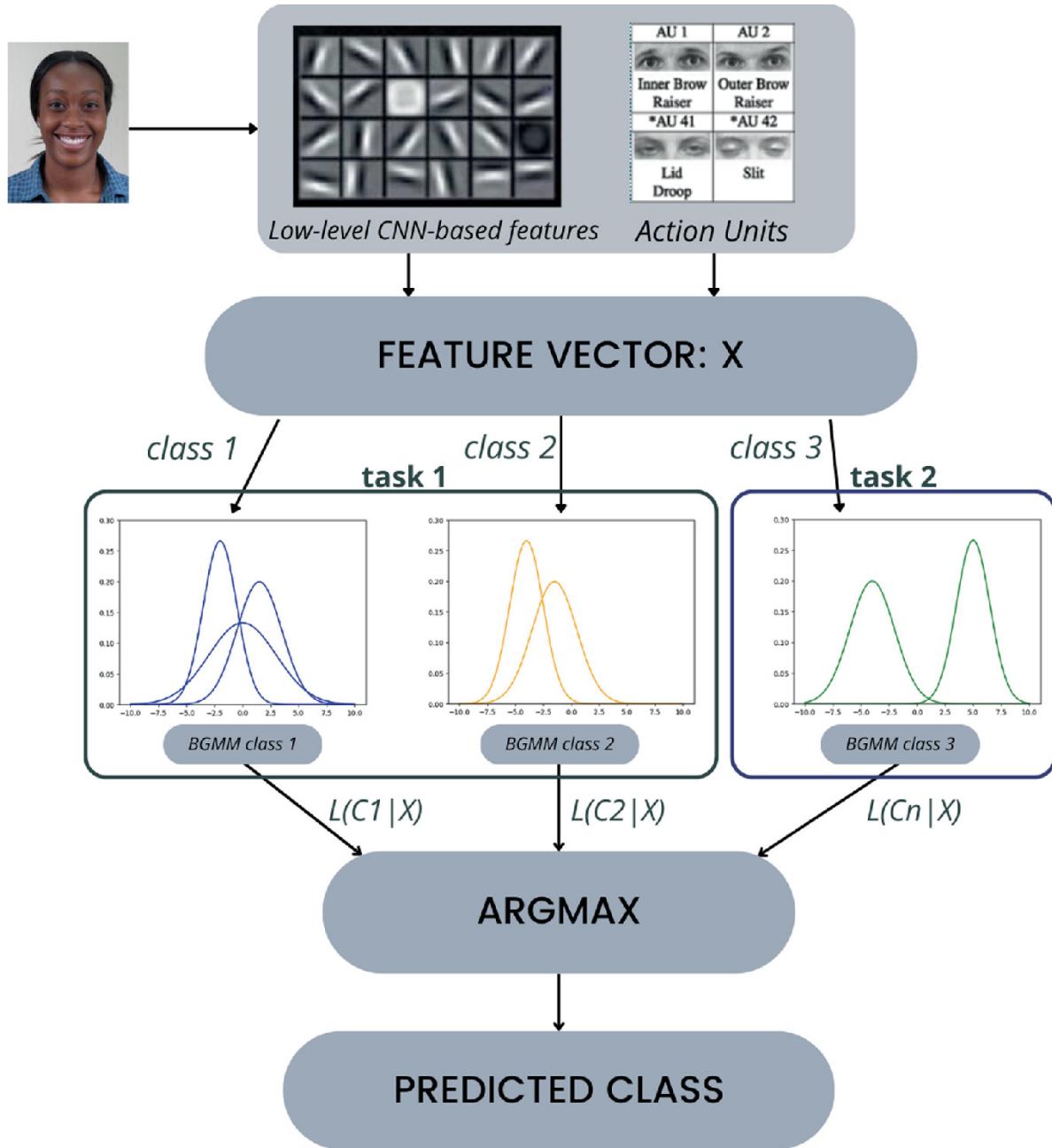


Fig. 3 Model architecture for 2 tasks (task1 = class1 + class2 and task2 = class3)

2.1.3 Algorithm

During training on the initial task, the different modalities are aggregated into a feature vector that is used to train the Gaussian mixtures. For this concatenation, we adopt a basic strategy: the low-level feature vectors are normalized between 0 and 1 and then combined with the high-level features to form a single vector containing both modalities.

After aggregation, the training dataset is divided into n subsets, each corresponding to one class of the initial task. These subsets are then used to train Gaussian mixtures.

Each mixture is trained with the Bayesian Gaussian Mixture approach [31]. We observed that using diagonal covariances matrices gives the best performance when using Bayesian Gaussian Mixtures as shown in Table 1. A complete covariance matrix overfit strongly and is not able to perform with the testing set. In contrast a simple variance producing spherical representation of data shows lower performances and the best performances are achieved with a diagonal covariance matrix.

Table 1 Accuracy of the combined features with different type of covariances, the diagonal covariances show the best performances for these features

Accuracy (mean \pm std)	Simple variance	Diagonal covariance matrix	General covariance matrix
Train	0.5838 ± 0.0087	0.6067 ± 0.003	1.0000
Test	0.5540 ± 0.0047	0.5850 ± 0.01	0.3745

For subsequent tasks, the same process is repeated while applying the same aggregation strategy. The Gaussian mixtures specialized in the new tasks are trained in the same way as for the initial task.

During inference, each facial image is processed by the feature extractors and aggregated following the same strategy as in training. The resulting feature vector is then passed through all Gaussian mixtures to compute the corresponding log-likelihoods. The mixture that produces the highest log-likelihood is considered the best match, and its associated class is returned as the model's prediction.

The training and inference algorithms of this architecture are presented below:

Training algorithm

Step

Operation

Input: Annotated dataset of facial expressions $D = \{(I, y)\}$

Output: Set of trained class-conditional BGMMs $M = \{BGMM_c\}$

- 1 Initialize $M \leftarrow \emptyset$ (dictionary of class → BGMM)
- 2 For each task T in D :
 - 3 If T is the first task, train CNN feature extractor F_{cnn} on $(I, y) \in T$
 - 4 Initialize $FeatureSet_T \leftarrow \emptyset$
 - 5 For each image I in T :
 - 6 $f_{CNN} \leftarrow F_{cnn}(I)$ (CNN feature vector)
 - 7 $f_{AU} \leftarrow OpenFace(I)$ (Action Units feature vector)
 - 8 $f \leftarrow \text{Concatenate}(f_{CNN}, f_{AU})$ (fused feature vector)
 - 9 Add $(f, \text{label}(I))$ to $FeatureSet_T$
 - 10 End For
 - 11 For each class c in $\text{Classes}(T)$:
 - 12 $F_c \leftarrow \{ f \mid (f, y) \in FeatureSet_T \text{ and } y = c \}$
 - 13 $BGMM_c \leftarrow \text{TrainBGMM}(F_c)$ (train class-conditional model)
 - 14 Add $(c, BGMM_c)$ to M
 - 15 End For
- 16 End For
- 17 Return M

Step	Inference algorithm	Operation
	Input: Dataset of facial expressions Dtest = { I }	
	Output: List of predicted labels Ypred	
1	Initialize Ypred $\leftarrow []$	
2	For each image I in Dtest:	
3	fCNN \leftarrow Fcnn(I) (CNN feature vector)	
4	fAU \leftarrow OpenFace(I) (Action Units feature vector)	
5	f \leftarrow Concatenate(fCNN, fAU) (fused feature vector)	
6	Initialize Scores $\leftarrow \{\}$ (dictionary class \rightarrow likelihood)	
7	For each (c, BGMM_c) in M:	
8	logL \leftarrow BGMM_c.logLikelihood(f)	
9	Scores[c] \leftarrow logL	
10	End For	
11	c \leftarrow argmax(Scores[c]) (class with maximum likelihood)	
12	Append c to Ypred	
13	End For	
14	Return Ypred	

2.2 Experimental Protocol

2.2.1 Continual Learning

Continual learning can be separated into different types of scenarios depending on how the set of labels and the amount of data points provided during each new task vary. In this study, we focus on a common scenario called Class-Incremental Learning. In this setting, tasks are presented to the model sequentially, and the model learns each task without access to the data from previous ones. Furthermore, the labels for each task are provided to the model for training but not in the inference phase.

Formally, the training set for a task t can be defined as $D_t = \{X_t, Y_t\}$ where X_t represents the data of a given task and Y_t the corresponding labels. We assume that each task follows a distribution $D_t := p(X_t, Y_t)$ and that there is no difference in distribution between training and testing sets. In this study, each task's data is assumed to arrive in a single batch.

Since our work focuses on facial expression classification, we divided the dataset into two parts. The initial task, used to train the feature extractor and initialize the Gaussian mixtures, consists of Ekman's basic expressions (joy, sadness, surprise, fear,

anger, disgust, and neutral). To organize the remaining classes into multiple tasks, we grouped the compound expressions according to their emotional proximity. We created incremental tasks corresponding to compound variants of joy, sadness, fear, anger, and disgust. This design allows us to evaluate how our architecture handles each family of basic emotions throughout the continual learning process. Based on this principle, the incremental tasks are defined as follows:

- **Compound joy:** happily surprised, happily disgusted, awed.
- **Compound sadness:** sadly fearful, sadly angry, sadly surprised, sadly disgusted.
- **Compound fear:** fearfully angry, fearfully surprised, fearfully disgusted.
- **Compound anger:** angrily surprised, angrily disgusted, hatred.
- **Compound disgust:** disgustedly surprised, appalled.

2.2.2 Datasets

To enable continual learning across a wide range of emotional expressions, we require an annotated dataset containing the target categories. For this purpose, we use the Compound Facial Expressions of Emotions (CFEE) dataset. It contains 5,060 images from 230 subjects, distributed across 22 classes. The images were collected in a controlled laboratory setting: each face is centered against a white background, and each subject displays several expressions. The subjects vary in both gender and ethnicity.

In terms of labeling, the dataset includes seven basic emotion classes (including neutral) and twelve compound emotion classes such as happily-surprised or angrily-disgusted. Although compound expressions are composed of multiple basic emotions, they are not merely the mechanical combination of facial muscle activations from their components. Instead, they are considered distinct, recognizable expressions that can be reliably used for model inference.

In addition to these nineteen basic and compound expressions, the dataset also contains three so-called complex emotions: appalled, hatred, and awed. While not formally categorized as compound expressions, they can be interpreted as combinations of multiple affective states. For instance, appalled may be described as fear mixed with disgust, hatred as strong anger combined with disgust, and awed as intense joy blended with fear. These associations are derived from the semantic meaning of the original English terms.

2.2.3 Metrics

Continual learning performance needs to be evaluated from three perspectives: overall performance across all tasks, memory stability on previously learned tasks, and learning plasticity on new tasks [35]. To address these aspects, we rely on three metrics.

The overall performance is assessed using Average Accuracy (AA) and Average Incremental Accuracy (AIA). Memory stability is measured using the Forgetting Measure (FM), which quantifies the average loss of performance on past tasks. Finally,

learning plasticity is measured using the Intransigence Measure (IM), which captures the impact of learning new tasks on model performance.

Average Accuracy (AA) at task k evaluates model performance across all tasks learned so far. It is defined as the mean test accuracy on all k tasks:

$$AA_k = \frac{1}{k} \sum_{j=1}^k a_{k,j}, \quad (1)$$

where $a_{k,j} \in [0, 1]$ represents the accuracy on the test set of task j after training on task k .

The Average Incremental Accuracy (AIA) represent a cumulative view of how AA evolves over time. It is defined as:

$$AIA_k = \frac{1}{k} \sum_{i=1}^k AA_i, \quad (2)$$

The stability of the model during continual learning is measured by the Forgetting Measure (FM), which evaluates how much accuracy the model has lost on previous tasks. It is computed by comparing the maximum performance of the model compared to the current performance.

For task j at step k , forgetting is computed as:

$$f_{j,k} = (a_{i,j} - a_{k,j}), \quad \forall j < k. \quad (3)$$

The FM at the k -th task is defined as:

$$FM_k = \frac{1}{k-1} \sum_{j=1}^{k-1} f_{j,k}. \quad (4)$$

A lower FM indicates a better ability to retain past knowledge and resist catastrophic forgetting.

The learning plasticity of the model, i.e. its ability to acquire new tasks, is evaluated using the Intransigence Measure (IM). This metric is defined as the difference between the performance of a jointly trained reference model and the performance of the continual learner:

$$IM_k = a_k^* - a_{k,k} \quad (5)$$

where a_k^* represents the accuracy of randomly initialized reference model trained on the joint dataset of all the previous tasks $\bigcup_{j=1}^k D_j$.

A lower IM represents a model that is able to not lose much accuracy between its continual learning performances and its normal learning performances.

All those metrics are shown in Table 2.

Table 2 Continual learning metrics

Measure	Role	Range	Optimization goal
Average accuracy	Measure the average performance so far	[0, 1]	Maximize
Average incremental accuracy	Measure the trend of improvement through the tasks	[0, 1]	Maximize
Forgetting measure	Measure how much the old knowledge is forgotten	[0, 1]	Minimize
Intransigence measure	Measure difficulty in learning new tasks compared to classical training	[0, 1]	Minimize

2.2.4 Protocol

For this experimentation, the first set of features, referred to as the deep features, is computed using the MobileNet model [16]. The architecture is modified so that the penultimate layer outputs a feature vector of 512 dimensions. The model is trained on the basic emotions using cross-entropy loss. After training the model to its best accuracy, the entire dataset is passed through the network to extract the embeddings from this layer.

The second set of features, referred to as the Action Unit (AU) features, is computed using the OpenFace tool [33], which provides 17 Action Units representing the activation of specific facial muscles for each subject.

The two feature vectors are concatenated to generate a third feature vector, referred to as the merged features. This merged vector is the primary representation used in our experiments, although we also evaluate the two individual feature sets to compare performance across modalities.

2.3 Experimental Results

In our approach, the initial task of emotion recognition contains the seven basic emotions. The accuracy of each feature type on these basic emotions is reported in Table 2 and shows that the performances are competitive with other models.

Throughout the continual learning process, as illustrated in Figs. 4, 5, and 6, accuracy decreases across all three feature representations. However, the merged feature vector combining the Action Unit features with the deep features extracted from the CNN consistently provides better performance. This concatenation yields a relative improvement of approximately 8% in classification accuracy across tasks, increasing from 0.530 with action units features alone to 0.575 with merged features, as shown in Table 3.

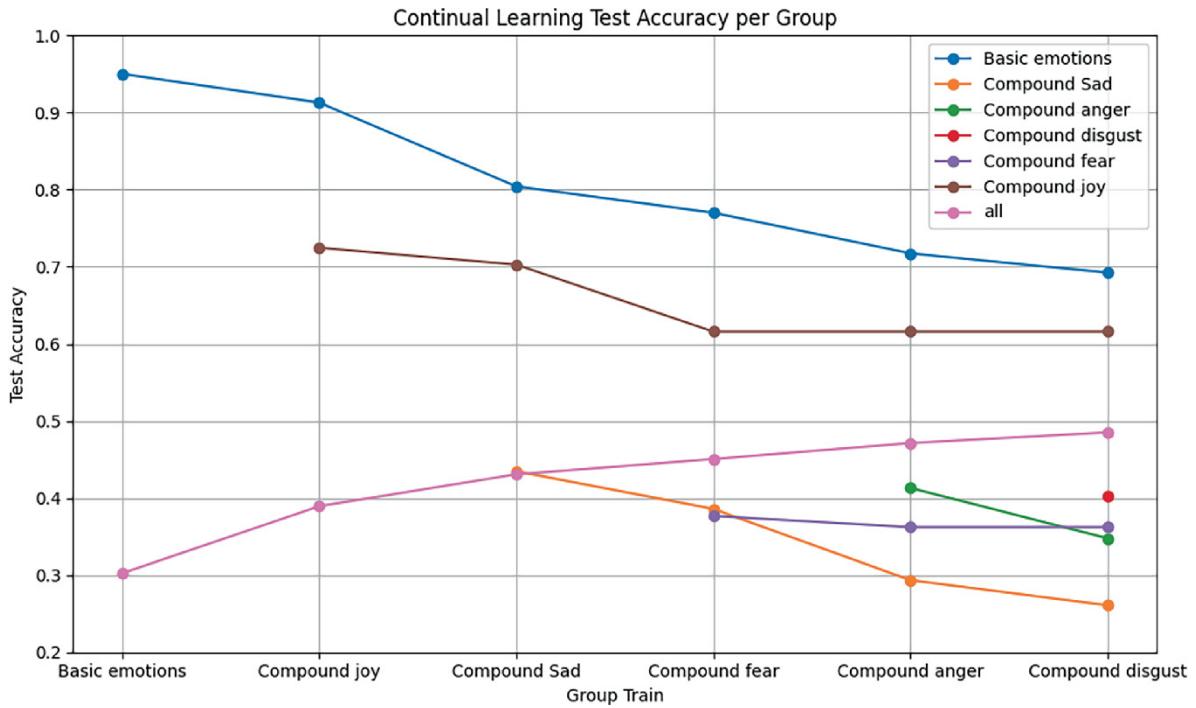


Fig. 4 Average accuracy of each task throughout the continual learning of the model trained on the deep feature vectors, showing the loss of accuracy on the older tasks

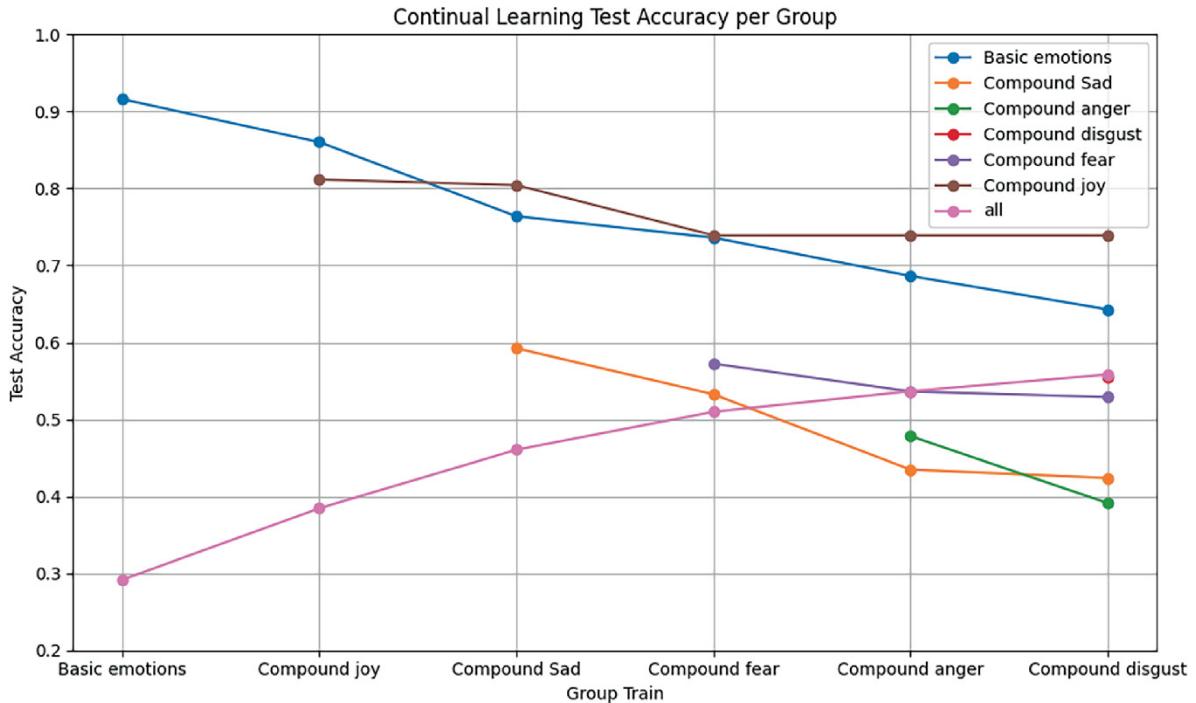


Fig. 5 Average accuracy of each task throughout the continual learning of the model trained on action units features, showing the loss of accuracy on the older tasks

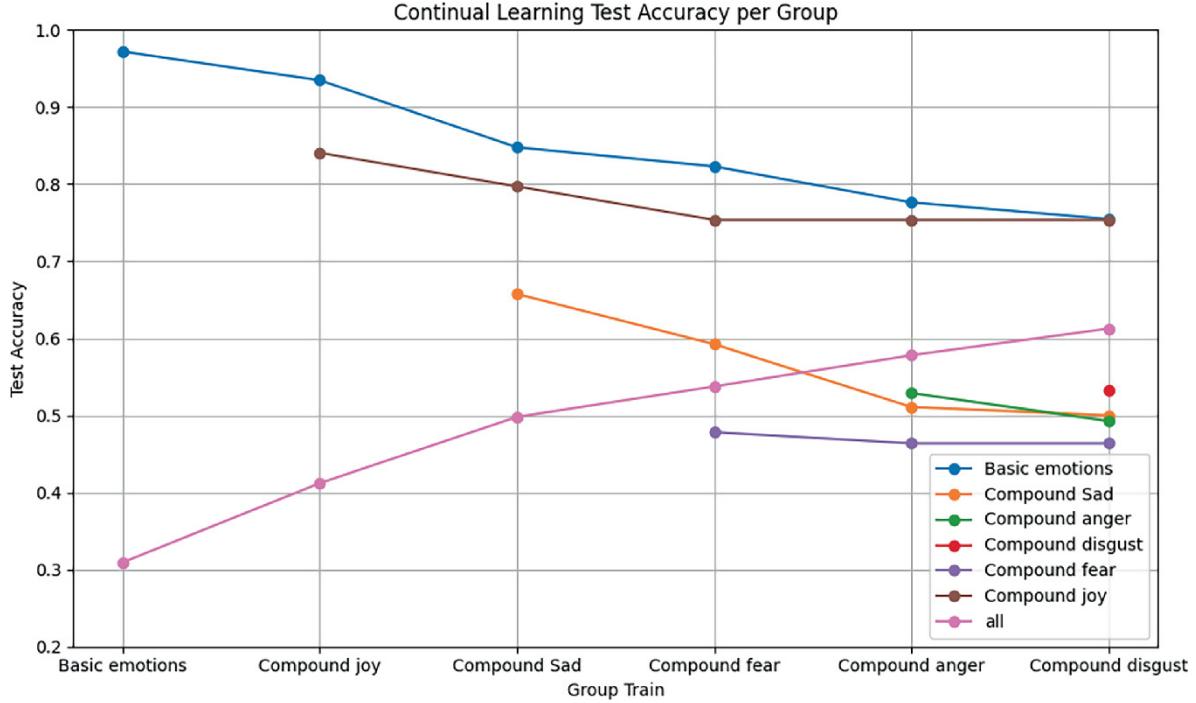


Fig. 6 Average Accuracy (AA) of each task throughout the continual learning of the model trained on merged feature s showing the improvement of the merged features in comparison to the sole Action Units or deep features

Table 3 Accuracy performances for each task at the end of the training

Accuracy (mean \pm std)	Basic expressions	Compound joy	Compound sadness	Compound fear	Compound anger	Compound disgust	All
Deep features	0.654 ± 0.09	0.635 ± 0.14	0.382 ± 0.1	0.384 ± 0.11	0.358 ± 0.07	0.496 ± 0.12	0.511 ± 0.05
AU features	0.653 ± 0.1	0.693 ± 0.06	0.405 ± 0.09	0.427 ± 0.07	0.352 ± 0.08	0.527 ± 0.09	0.530 ± 0.05
Merged features	0.744 ± 0.02	0.705 ± 0.03	0.467 ± 0.03	0.441 ± 0.04	0.378 ± 0.03	0.496 ± 0.04	0.575 ± 0.01
Relative evolution	+ 13%	+ 1%	+ 15%	+ 3%	+ 5%	-5%	+ 8%

Figures 7, 8, and 9 present the performance of the model using three incremental metrics: Average Incremental Accuracy, Forgetting Measure, and Intransigence Measure. These metrics respectively capture the evolution of accuracy during continual learning, the stability of the model in retaining knowledge from previous tasks, and the ability of the model to acquire new information during training. Across all three graphs, the concatenation of deep features and Action Unit features consistently yields the best results.

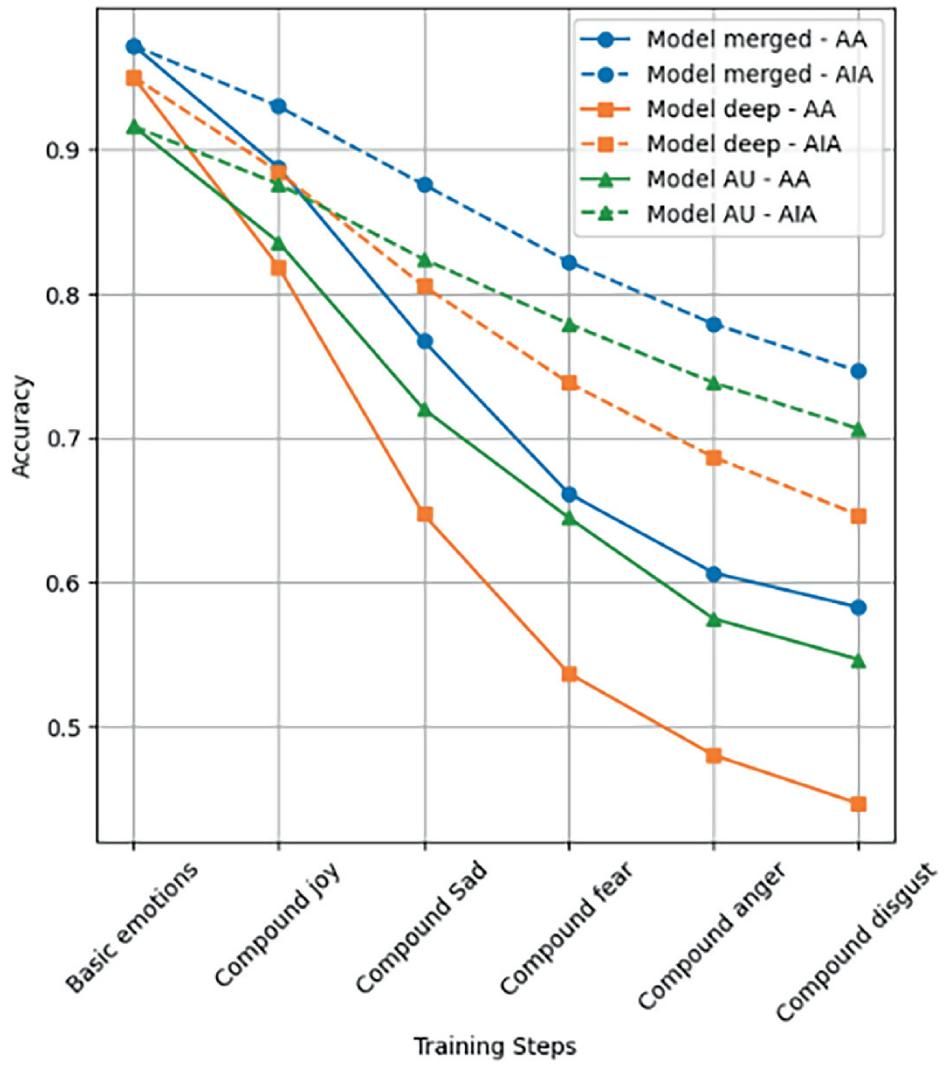


Fig. 7 Average Accuracy (AA) and Average Incremental Accuracy (AIA) throughout the continual learning process for the three feature vectors. Showing the best performances for the merged features in Average Accuracy and Average Incremental Accuracy

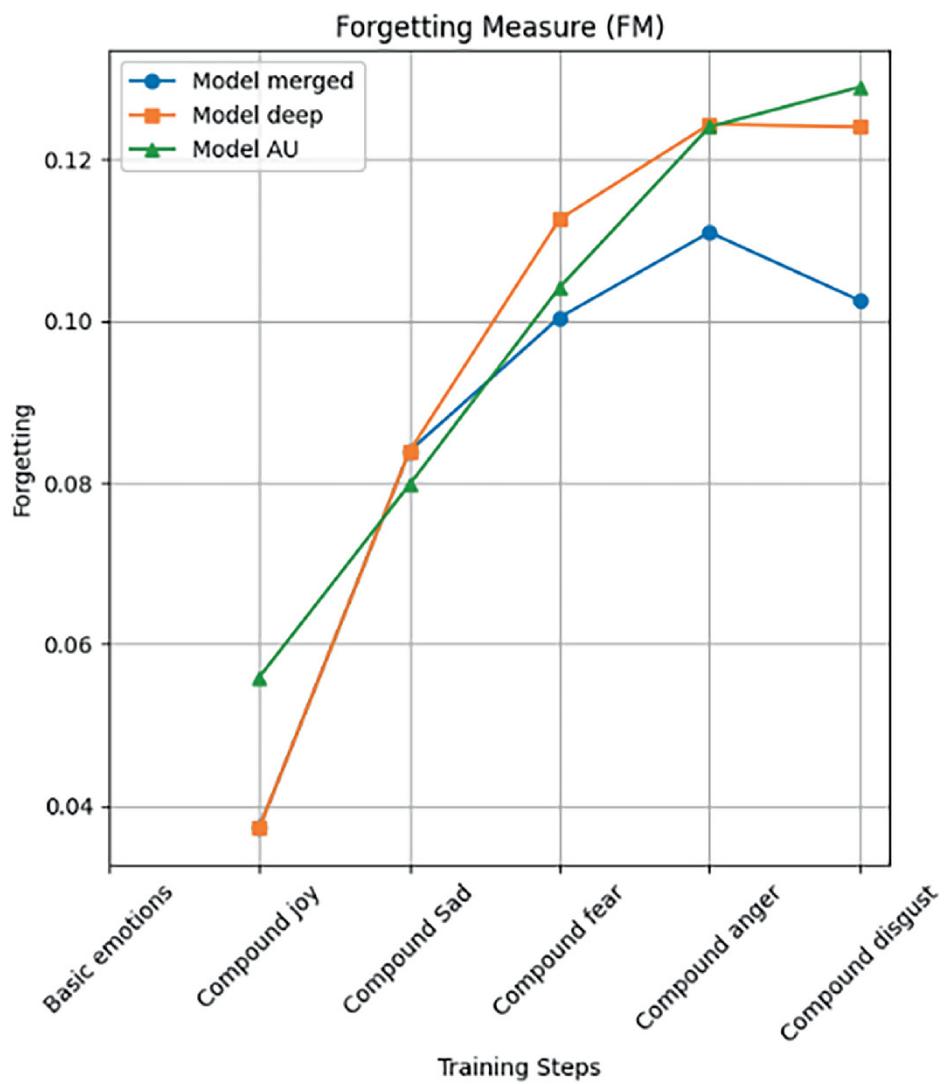


Fig. 8 Forgetting Measure (FM) across the continual learning process for the three feature vectors. The results indicate that the merged feature representation mitigates forgetting more effectively than individual feature types

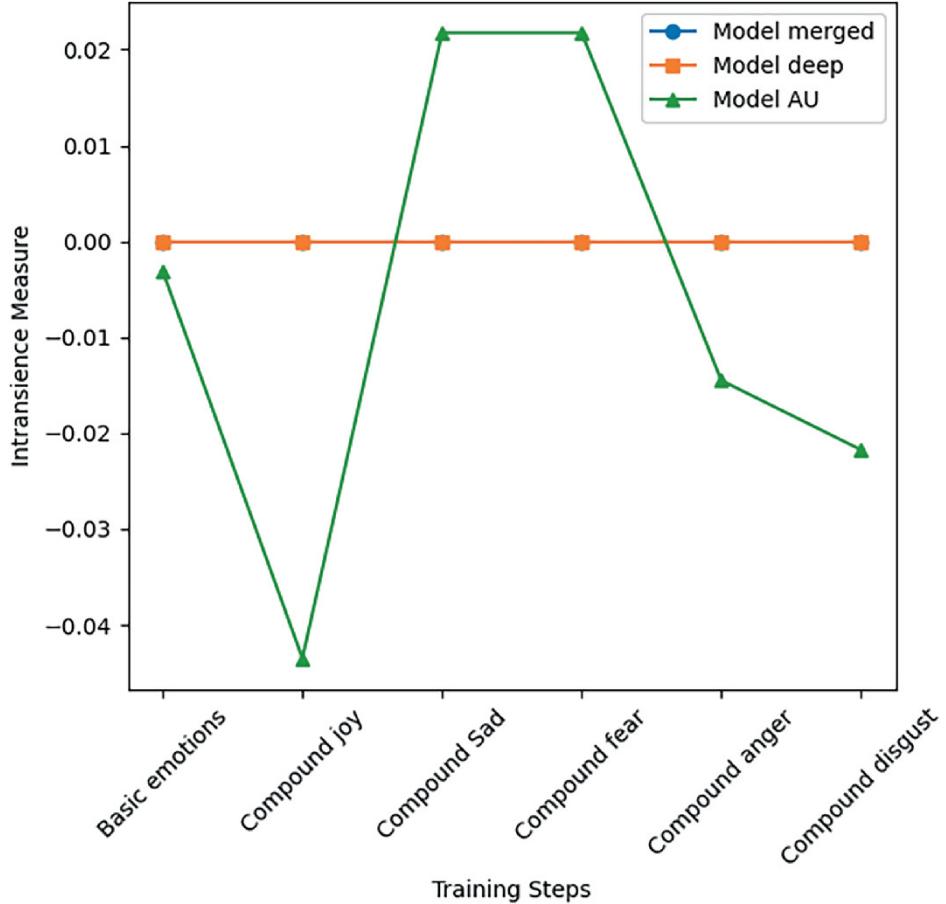


Fig. 9 Intransience Measure (IM) across the continual learning process for the three feature vectors, indicating that the addition of new tasks has a negligible effect on the model’s performance

In Fig. 7, we report both the Average Accuracy and Average Incremental Accuracy of the three feature representations. The concatenated features show clear improvements in both metrics. While the deep features achieve strong performance on the initial task, their accuracy declines steadily during continual learning. This behavior is expected, since the deep features were extracted from a model trained exclusively on the initial task and thus generalize poorly to new tasks. In contrast, the Action Unit features start with lower performance on the initial task but degrade less across incremental tasks. The combined features, however, capture the strengths of both representations: they perform well on the initial task and retain stronger performance throughout continual learning. This demonstrates that the BGMM can effectively leverage the merged feature vector to infer the correct labels, even when the features are not produced by a model specialized for those classes.

Figure 8 shows the average forgetting of our approach on the three feature vectors. We observe lower forgetting with the concatenated feature vector, which indicates less performance loss on previous tasks during the continual learning process. The purpose of this metric is to highlight the stability of the proposed architecture. We can see that the merged features start with the same level of forgetting as the deep features on the first incremental task but gradually forget less than the two individual feature vectors

as training progresses. This demonstrates that the combined features are more resilient than the separate vectors throughout the continual learning process.

Figure 9 shows the intransigence performance of the model during continual learning across different tasks. Since our approach learns each class probability distribution separately, it does not suffer from accuracy loss due to the continual learning process. As a result, the Intransigence Measure remains equal to or close to zero for all feature vectors. This reflects the ability of the proposed architecture to maintain separate representations for each class. Consequently, the number of tasks and their order do not influence the performance of the architecture. The only task with a strong impact on overall performance is the initial task, because the CNN used for deep feature extraction is trained on this smaller set of labels. A reduced label set lowers the quality of the extracted feature vector and thus affects the full model performance.

For each incremental metric, our approach achieves better performance than the individual feature vectors. The combined feature representation is able to compensate for the weaknesses of each separate modality. The proposed architecture suffers less from catastrophic forgetting, maintains higher accuracy, and does not experience performance degradation due to the continual learning setting. These results demonstrate the capability of our approach to effectively address the continual learning problem in Facial Expression Recognition.

3 Discussion

Each feature type exhibits different strengths and weaknesses. Figure 1 illustrates which features perform better for each expression. In the last row, negative values correspond to classes where the Action Unit features predicted the correct label while the deep features did not, and positive values indicate the opposite case. We observe that the deep features perform better on the basic expressions of the initial task but show weaker results on compound expressions. In contrast, the Action Unit features generally perform better on compound expressions, apart from the “appalled” class.

This outcome is consistent with expectations: deep CNN features, trained specifically on basic expressions, achieve higher accuracy on those categories but generalize poorly to compound ones. Conversely, Action Unit vectors, which encode facial muscle activations, demonstrate more stable performance across tasks (Fig. 10).

	neutral	happy	sad	fear	angry	surprise	disgust	Result on test by class	Happily surprised	Happily disgusted	Sadly fearful	Sadly angry	Sadly surprised	Sadly disgusted	Fearfully surprised	Fearfully disgusted	Angrily surprised	Angrily disgusted	Disgustedly surprised	Appalled	Hatred	Awe	
	Full Features	45	44	40	11	31	37	22	44	42	26	23	30	17	22	25	28	32	15	34	14	15	25
Deep Features	45	41	38	11	31	39	26	37	35	23	24	24	13	17	19	19	31	6	30	15	13	22	
AU Features	39	40	24	16	23	27	21	45	39	20	23	26	14	23	27	26	28	23	27	1	18	21	
Deep - AU Features	6	1	14	-5	8	12	5	-8	-4	3	1	-2	-1	-6	-8	-7	3	-17	3	14	-5	1	

Fig. 10 Difference in correctly recognized test samples between the deep feature model and the AU model on the CFEE dataset, highlighting that deep features perform better on basic expressions, while AU features show superior performance on compound expressions

We also evaluated how our approach compares to an idealized scenario in which, between the two feature sets, the model always selects the best-performing one. To simulate this, predictions were generated using both models, and a sample was considered correct if either of the feature-based models produced the right label. As shown in Table 4, while the merged features outperform each feature set individually, they still fall short of the performance achieved by this best potential baseline. This gap is likely due to the simplicity of the concatenation strategy used in our current implementation.

Table 4 Final and potential best accuracy of the model through different features

Metric	Merged features	Deep features	Action unit features	Potential best features
Test accuracy (mean \pm std)	0.614 ± 0.01	0.552 ± 0.02	0.545 ± 0.04	0.738 ± 0.03

4 Limitations and Future Work

Our current architecture has several limitations. First, it relies on a large initial task to train the CNN feature extractor. This dependency reduces the flexibility of the continual learning analysis, since performance in later tasks is strongly influenced by the first training step. In future work, we plan to explore other types of feature extractors and descriptors, such as Histogram of Oriented Gradients (HOG) or Local Binary Patterns (LBP), to reduce this reliance and diversify the extracted representations.

A second limitation is the feature fusion strategy, which is currently restricted to simple concatenation. While this provides an initial proof of concept, it does not fully exploit the complementarity between modalities. Future work will therefore investigate more advanced fusion methods, such as dimensionality reduction (e.g., PCA) or dynamic weighting mechanisms, to better emphasize the most informative components

of the feature vectors. These strategies may further improve performance, particularly for continually learning on complex compound expressions.

Finally, our experiments were conducted on the CFEE dataset, which contains numerous labels and was collected under controlled conditions, making training and evaluation easier. However, this dataset does not capture the variability of real-world scenarios. As a next step, we plan to extend our experiments to more challenging datasets such as RAF-DB, which include greater diversity in pose, illumination, and occlusion, thereby allowing us to evaluate our approach under more realistic conditions.

5 Conclusion

In this work, we introduced a modular architecture for facial expression recognition (FER) in a continual learning setting. Our approach combines deep features extracted from a CNN with Action Units (AUs) to build a hybrid representation of facial expressions. This is then modeled using an ensemble of Bayesian Gaussian Mixture Models with each one conditionally trained on an emotion class. This architecture allows the system to incrementally acquire new emotional categories, including compound expressions, while effectively mitigating catastrophic forgetting, which is a core challenge in continual learning.

Through experiments conducted on expression-specific datasets Compound Facial Expression of Emotion (CFEE), we showed that aggregating different feature types leads to more accurate performance during the continual learning process. The merged feature consistently outperformed models based on individual feature types across all evaluated metrics. While our current concatenation strategy provides encouraging results, it does not yet match the potential upper bound where the most informative modality is always selected.

This work contributes to the development of adaptive and emotionally intelligent systems that can evolve without the need for retraining on all past data. In future work, we aim to explore more advanced feature aggregation mechanisms to further enhance performance in dynamic and unconstrained real-world environments.

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Advanced Techniques in Facial Landmark Detection and Feature Extraction for Emotion-Aware AI Systems

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Abstract

Emotion-Aware AI systems, behaviour perception and understanding leveraging large-scale facial data to include learning-based Facial Landmark detection; Attribute Error: ‘None Type’ object has no attribute ‘shape’. This chapter discusses the state-of-the-art advanced techniques to find these important facial landmark points such as corners of eyes; tip of nose and different lip contours used for emotion modelling. We conduct an extensive survey of traditional as well as modern localisation methods with the help of deep learning such as Active Shape Models, Active Appearance Models (AAM), Convolutional Neural Networks for heatmap regression and attention mechanism to enhance the efficacy in performing localisation. Likewise, the chapter presents classical feature requirements such as LBP and HOG as reverse roles of low-level visual processing while also

describing recent deep embeddings for facial texture, shape and dynamics depiction. Emphasis is placed on cross-condition performance testing illumination, head pose and occlusion, ethnicity. We also discuss the real-time use-cases, and associated implementation challenges and optimization approaches for achieving this empirical deployment across edge-AI scenarios/concerns, small device mobile environments. Furthermore, a review of present benchmark datasets and benchmarks is included and how to implement trustworthy emotion-capable AI pipelines. Combining traditional approaches with the contemporary deep learning models the explanations in this chapter provide specific guidance to researchers aiming at building efficient and reliable emotion-recognizing systems.

Keywords CNN-based detection – Emotion recognition – Feature extraction – Facial landmarks – Heatmap regression – Pose invariance

1 Introduction

1.1 Importance of Facial Analysis in Emotion-Aware AI

Facial analysis also plays a key role that enables the machines to identify and perceive human emotions without being invasive and in real time. Human face micro expressions are rich affective cues that reflect micro movements, muscle activities and dynamic formations that are strongly associated with interior emotional states. Past studies have shown that non-verbal communication forms a significant portion of human communication and facial expression plays a crucial role in providing critical context to verbal communication [1]. Facial signals can be applied in the domain of AI so as to better and customized human–machine interactions, combined with the advantages of naturalness, compassion, and adaptability, and play a key role in the domains of assistive technologies, driver monitoring, and social robotics.

Moreover, facial recognition is more direct visual as compared to speech or physiological detectors, and this makes it less intrusive and scalable. Advances in and computer vision and deep learning have achieved levels of facial landmark detection and feature extraction to such high standards, that we can now make strong inferences of emotion even in rather poor conditions [2]. As cameras (e.g., in smartphone, vehicle, or IoT devices) are more widespread, facial analysis is a feasible situational awareness

modality, emotion-driven personalisation, as well as context-sensitive system signals, in both consumer and industrial contexts.

1.2 Objectives of the Study

The aim of this study is to provide a critical and detailed and systematic review of advanced methodology of face landmark detectors and feature extractors specifically to support the emotion conscious AI systems. Both classical approaches, as well as novel deep architecture, are created and trained. The second objective is to present performance trade-offs and field experience and integration strategies to the Indian pipelines of emotion recognition.

The study is also intended to offer guidance to the researcher and practitioner by identifying the best practices, paradigm comparison, and unresolved issues. We aim to provide the appropriate datasets, benchmarking procedures, and evaluation measures to ensure that the readers can reasonably evaluate, as well as enhance state-of-the-art systems. Lastly, we will work on promoting better comprehension of how these systems can be deployed to real-world applications with limitations like computational resources, privacy, and cross-cultural variability.

1.3 Applications in Real-World Systems

The facial landmark recognition and emotion-aware AI have been used in numerous fields. Automatic emotion recognition is applied in health care to either track patient mood, indicate depression or aid in autism therapy with feedback about emotional conditions [3]. Facial analysis work may also be utilized in mental health analytics, such as to continuously measure the emotional valence in a therapy session or telehealth context [4]. In learning environments, where the frustration, engagement or boredom of learners is identified, adaptive tutoring systems can modify the pace of pedagogy or content [5].

In smart self-driving cars and autonomous vehicles, facial-read driver stress, fatigue, or distraction can be detected, and, in autonomous driving, safety measures can be taken around drivers, as well as human connection to the vehicles. Facial emotion AI finds its application in marketing and advertising as well: analysing the reactions of the audience in real-time, systems can personalize the content or measure the success of the campaign [6]. Besides, facial analysis can be used in entertainment (VR/AR, gaming,

social robots); to make the avatars or agents act according to the mood of the users. This is because machine identity verification in the wild will persistently require the combination of face landmark recognition and effective feature integration to create responsive and context-sensitive AI systems [7].

2 Fundamentals of Facial Landmark Detection

2.1 Advanced Techniques in Facial Landmark Detection

Facial landmark detection can be described as the process of locating certain key points (landmarks) on a human face including the corners of the eyes, tip of the nose, and corners of the mouth to obtain facial geometry in a small and structured way. Such landmarks have been used as anchors to downstream tasks like face alignment, expression analysis, head pose estimation and emotion inference. Facial landmarks can offer a semantic cognizant scaffold that allows algorithms to make inferences about shape transformations, relative motion and local appearance variations. Recent papers have provided increasingly accurate and efficient landmark detection models: e.g., Hong and Lin [8] introduce a knowledge distillation method that replenishes the knowledge of the large models to small ones without introducing the detection precision in small gadgets [8]. Equally, another model called Efficient Facial Landmark Detection (EFLD) was proposed by Wu, who achieved a high level of landmark localization specifically to work with embedded systems through a lightweight backbone and cross-format training approach [9]. Collectively, the above developments underscore the changing significance of landmark detection as the initial step in the current facial analysis pipelines (Fig. 1).

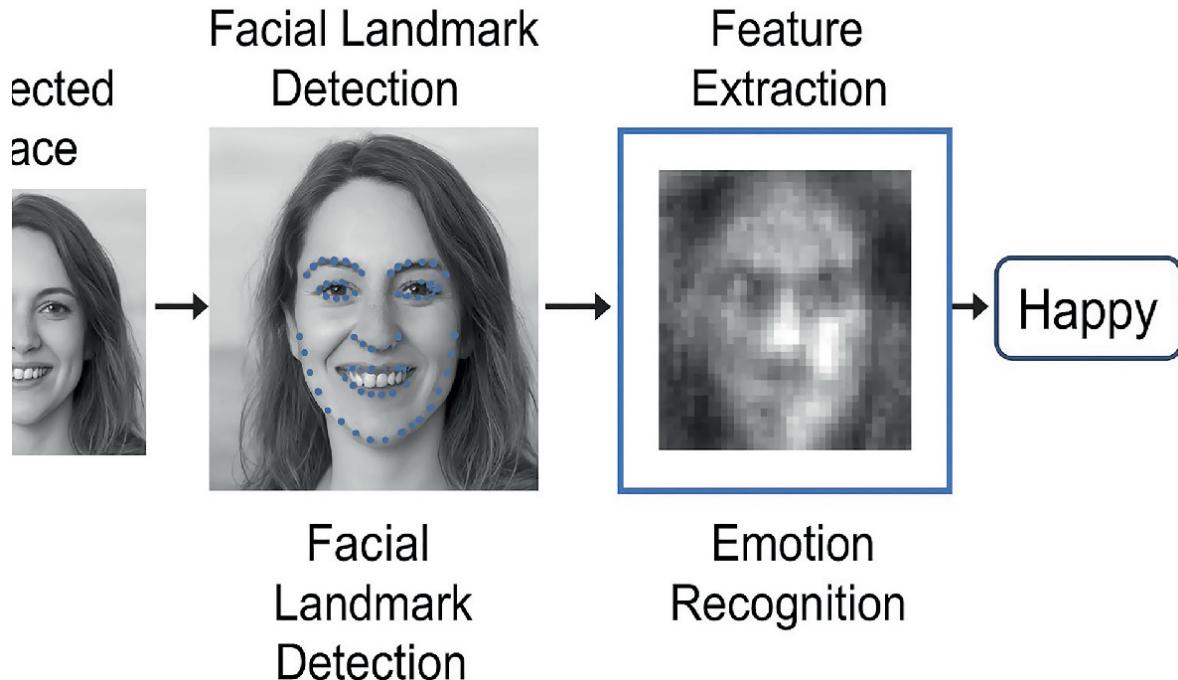


Fig. 1 Advanced techniques in facial landmark detection and feature extraction for emotion aware AI systems

The figure depicts the top-level view of the end-to-end pipeline of emotion-conscious AI systems, in which it has been highlighted the role of the facial landmark detecting and feature extraction in identifying human emotions. It commences with an acquired facial image which is usually through camera vision systems. The stage of landmark detection on the face refers to determining the most important structural features (such as the eyes, nose, lips and jawline) to project the distinct geometry of the face. These landmarks serve as important reference signals to the next stage of feature extraction, where pixel or region-based features are calculated, typically through geometric, appearance-based or deep learning features, to compute non-trivial representations of facial expression. These features are lastly inputted into an emotion recognition model that then is used to classify the seen expression (e.g., “Happy” through trained classifiers or deep networks). This modular flow is not only capable of interpreting emotions in real time but is also robust and adaptable to be applied in human–computer interaction, affective computing and intelligent surveillance. The illustration is successful in producing the contribution of organized face recognition to emotionally intelligent AI systems.

2.2 Common Landmark Points (e.g., Eyes, Nose, Mouth)

Some common sets of points are often labelled in datasets and models in facial landmark detection, often including the eyes (inner/outer corners, eyelids), eyebrows (arch line), nose (bridge, tip, nostril boundaries), lips (corners and contours), and the jawline or chin. These reference landmarks allow a system of consistency in reference between faces. To illustrate this, Huang et al. [10] report the lightweight key point detector that uses regression and heatmap supervision to precisely detect such typical facial key points in highly misleading scenarios such as masking or changes in pose [10]. Their findings reveal the extent to which the strength of localization of landmarks in these major regions of the face can be beneficial in downstream tasks such as recognition of expressions or face alignment. Besides, according to a recent report of surgical cases evaluation in changing conditions provided by Frajtag et al. [11], the algorithms were shown to be reliable in detecting landmarks such as ears corners and nose tip to allow its usage safely in the future [11]. Through that, these conventional landmarks remain the crucial element in the process of designing and benchmarking facial analysis systems (Table 1).

Table 1 Key facial landmarks and their functional relevance in emotion analysis

Region	Landmark points	Description	Associated emotions	Relevance score (High/Med/Low)	Application context
Eyes	Inner/outer canthus, eyelids	Detects blinking, gaze shifts	Surprise, fear, happiness	High	Eye tracking, fatigue detection
Eyebrows	Arch, inner/outer brow	Indicates stress or surprise	Anger, sadness, surprise	High	Emotion labeling, HCI
Nose	Nose tip, nostril edges	Minor expression role	Disgust, neutral	Low	Face alignment, identity verification
Lips/mouth	Corners, upper/lower lips	Critical for smile/frown cues	Joy, sadness, disgust	High	Emotion scoring, speech sync
Jawline	Chin tip, jaw angle	Affects facial geometry	Tension, fear, determination	Medium	Head pose estimation
Forehead	Mid-brow, upper brow line	Shows wrinkle patterns	Surprise, confusion	Medium	Stress detection

2.3 Dataset Annotations and Landmark Standards

With facial landmark detection problems, the datasets must be familiar and trusted in terms of their annotations that indicate exactly the location of each landmark within facial geometry. A typical procedure is that a fixed set of landmarks (e.g. 68-point, 98-point or 106-point scheme) is mended and uniformly applied in all images so that identities can be extrapolated using models. When consensus correspondence (e.g. with Procrustes analysis) is used to reduce inter-annotator error, they are typically customarily marked out by expert manual labelling or semi-automatic methods. Some datasets like 300-W, WFLW use the 68-point scheme, and some extend to profile views using defined landmarks such as Menpo. Metadata relating to visibility, occlusion and landmark confidence are also a good annotation standard. These annotation conventions allow the use of consistent evaluation metrics (including normalized mean error, area under curve, and failure rate) between studies and make it possible to benchmark and compare methods. The annotation standard consistency is what allows one to compare fairness among algorithms and transfers between datasets.

3 Classical Approaches to Landmark Detection

3.1 Active Shape Models (ASM)

One of the early statistical models of shape modelling and fitting (such as faces) is Active Shape Models (ASM), which trains a point distribution model (PDM) based on annotated training shapes and then refits the shape to match image features. ASM uses local adjustment of all landmarks (e.g. along a normal profile or gradient) and controls them constrained with a set of global shape variables to stay within plausible variation based on PCA. The tradeoff between local feature matching and global shape constraints enables ASM to impose consistent facial geometry to the image data fitting. There has been more recent investment in the revisiting of the concept in a parametric or hybrid form; a recent 2025 paper has a parametric ASM implementation which encloses cascade regression into the ASM model in order to enhance efficiency and compactness in facial landmark detection [12]. Although it has benefits, ASM may not be able to cope with significant changes of pose or elaborate variation of texture.

3.2 Active Appearance Models (AAM)

With the Active Appearance Models (AAM), ASM is extended to model shape and texture (appearance) change in the joint generative model. Both the shape of landmarks and the form of the distorted texture (to a canonical shape) are parameterized in AAM and the parameters are updated iteratively (often by gradient descent or Gauss Newton) to reduce the discrepancy between the appearance of the image and the appearance of the model. This joint modelling has more powerful constraints and may have more precise fits particularly in rather controlled imaging situations. Since shading, texture and variance of intensity are conveyed through the appearance component, AAM can be better adapted to detail of subtle surface features in the face [13]. Nevertheless, AAM fitting is computationally intensive and is susceptible to both initialisation and light variations.

3.3 Constrained Local Models (CLM)

Constrained Local Models (CLMs) combine global shape constraints with local appearance models (patch experts) that evaluate likelihoods of landmark positions in local neighbourhoods. Each local patch detector proposes candidate positions, and these local responses are combined under a global shape prior (often via optimization such as mean-shift) to enforce anatomical consistency. CLMs thus enjoy robustness to local variations such as partial occlusions or local texture noise while maintaining structural coherence. An enhanced example is the Convolutional Experts CLM (CE-CLM), which integrates convolutional local detectors with expert mixtures within the CLM framework, achieving state-of-the-art alignment especially for profile faces [14].

3.4 Limitations of Classical Methods

Traditional landmark classification techniques like ASM, AAM and CLM encounter a number of constraints on their in-the-wild application. In the first place, they are limited to linear PCA models and, as such, cannot capture complex non-linear facial deformations, as are found in different expressions and extreme poses. Secondly, they are usually sensitive to good initialization and are slow to draw near the true face in cases that the initial guess is distant, and hence are fragile in practice. Third, they are more susceptible to changes in illumination, occlusions (e.g., hair, glasses) and texture noise as they do not behave well in those cases due to the vulnerability of their local detectors or profile matching. Inter-demographic

and inter-imaging weaknesses Generalization to diverse demographics and imaging conditions is another weakness: classical methods typically cannot be easily scaled to large and diverse data without hand-tuning [15]. Lastly, their respective iterative fitting is computationally expensive, so they will not be well suited to run in real time or with limited resources.

A holistic hierarchical view of the complexes that are normally encountered in the facial landmark detection systems and the mitigation measures that can be adopted is provided in the below figure christened Common Challenges in Facial Landmark Detection and Suggested Mitigations. The roofline lists five major barriers: occlusion, head position variability, ethnic and cultural bias, real time options and low light/noise- all high impact items to the nature and strength of the localization of landmarks in uncontrolled environments. These barriers result in a more central block that can be referred to as Mitigation Techniques which highlights the need to have a combined strategic response. According to this block, the diagram is divided into four large areas of solution, i.e., Data Augmentation, Robust Algorithms, Multi-modal Fusion and Hardware Optimization. These areas are also further broken down into techniques that can be applied individually such as image improvement, ensemble techniques, 3-dimensional modelling and adaptive thresholding which are effective tools that can be employed to improve model performance and accuracy. This visual overlay highlights the depth of face landmark issues in the real world, and why algorithmic, architectural and data-centric refinements must be made in order to establish workable and trustworthy facial analysis systems (Fig. 2).

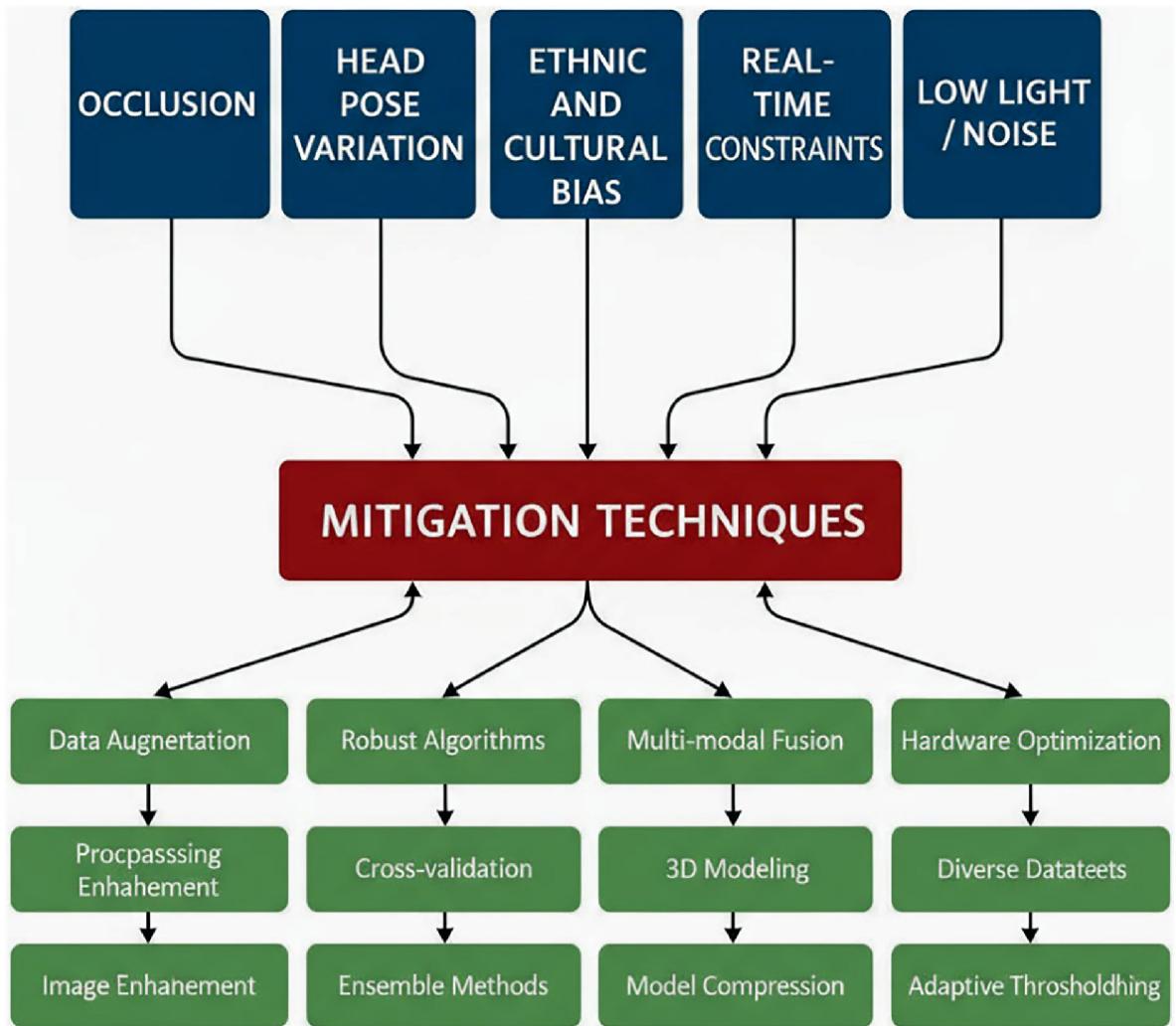


Fig. 2 Typical issues with facial landmark detection and recommended mitigation

4 Deep Learning-Based Landmark Detection

4.1 Convolutional Neural Networks (CNNs)

Since then been replaced by convolutional Neural Networks (CNNs) that have become the de facto minimal design architecture of facial landmark detection compared to older regression or template-based methods. To learn hierarchical features (that is, first the edges, then the facial structures) CNNs are trained on raw patches of images or on whole crops of face using several convolutional and pooling layers. These trained features are next projected to land mark coordinates by fully connected layers or regression heads. The deep features are able to record strong patterns of appearance variation based on changes in lighting, pose, and expression. An example is a study of

facial landmarks detection and image processing which showed that convolutional frameworks, particularly the variant of ResNet, are more accurate compared to cascade regression in adverse environmental factors. CNNs are still popular in mobile or real-time systems due to their ability to be optimized using quantization, pruning, or compact backbones without leading to misleading landmark localizations when used in highly unconstrained in the wild scenarios.

4.2 Heatmap Regression Models

Heatmap regression has become an effective face landmark detection paradigm that learns regression of wards into dense pixel-by-pixel prediction. Instead of simply producing the values of coordinates, the network produces a heatmap at a single location per landmark containing the intensity of the pixel indicating the likelihood of the landmark at that location. After that, the coordinate is chosen as the position of the largest response (argmax) or through a differentiable approximation such as Soft argmax. Another recent work Heatmap Regression without Soft-Argmax to do facial landmark detection [17] suggests a different structured prediction objective that uses no Soft argmax nor requires Soft-argmax to converge to the state-of-the-art on tasks like WFLW and 300 W [16]. Heatmap approaches are outstanding in the modelling of uncertain spatial information, aesthetic neighborhood and provide more localization consistency within a network of occlusions or subtle variations compared to direct regression networks.

4.3 Attention Mechanisms in Facial Detection

The attention mechanisms have also been used to enhance the facial landmark network by making the models focus on the spatial regions or channels selectively that can be used to localize the Landmarks. Spatial or channel attention modules can dynamically weight features in landmark detection tasks so that such important parts of the face as lips, eyes or nose are emphasized and decoded at different conditions. In general, Attention-based Face Alignment investigates the benefits of attention modules in convolutional models in improving localization accuracy in the presence of pose and lighting change. The other method is Selective Cascaded Regression with Patch Attention that applies patch-level attention to regress more challenging landmarks by focusing on the most-informative local

patches at successive steps. These attention-based mechanisms enhance robustness to background clutter, occlusion and misalignment by adjusting identically with highlighting relevant parts and eliminating irrelevant details on a layer-by-layer basis.

4.4 Lightweight and Real-Time Models

The application of facial landmark detection in real-time systems like mobile, embedded or edge devices needs models to be computationally efficient, low-latency and light on memory without compromising on accuracy. Some of the methods that contribute to this trade-off include model pruning, quantization, knowledge distillation, and efficient architecture design (e.g. MobileNet, EfficientNet backbones). The hybrid architecture that shares CNNs with lightweight architecture or coarse-to-fine prediction heads have also been discovered to be promising. One such work is the piece by CNNs and Markov-like Models to Facial Landmark Detection: a hybrid model that restricts the number of landmarks in the model as well as adding the spatial consistency penalty to simplify the model without compromising accuracy. More intelligent heatmap-based models like PIPNet can eliminate the inference bottleneck by inference and score at sub-resolution feature maps, so no high up sampling rates are needed and can run at tens of frames per second on both GPUs and CPUs. The viability of precise and real time identification of facial features in resource-limited environments is brought to light by designs such as these [17].

5 Feature Extraction Techniques

5.1 Geometric-Based Feature Extraction

A geometric-based feature extraction emphasizes on the spatial association of facial landmarks (distances, angles, ratios, triangulations) to encode the shape and relative arrangement of facial features. These characteristics are necessarily interpretable, compact and robust to the changes of moderate light conditions and they are useful in emotion recognition systems. As an example, Murugappan et al. apply to the feature sets based on the landmark a triangulation method by constructing triangles between selected Action Units (AUs) and calculating their inscribed circle area and triangle area to differentiate the feelings in real-time. PLOS.

5.2 Appearance-Based Techniques (HOG, LBP)

Appearance-based feature extraction computes local texture or gradient patterns of patches on face images to extract descriptors, to describe fine-grained texture and shading variation related to motion of facial muscles. There are two popular methods: Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP). The HOG descriptor also quantifies the gradient orientation distributions within local cells which makes it resistant to illumination, local replacements and illumination variations.

5.3 Deep Feature Embeddings (e.g., VGGFace, FaceNet)

Deep feature embeddings are vectors of high dimensionality, semantically meaningful feature vectors encoding both facial identity, texture, and structural details by using pre-trained deep neural networks (which are most frequently face recognizing). They can also be extended by such embeddings that can be fine tuned to perform tasks like emotion recognition, or they can be combined with landmark features. As an example, in Deep learning of facial embeddings and facial landmark points to recognise emotion the authors examine how FaceNet embeddings can be used in conjunction with landmark features to achieve more accurate results in emotion recognition.

5.4 Temporal Feature Extraction for Video Streams

Temporal feature extraction encodes the dynamic changes in face expressions over video frames to allow the emotion recognizers to utilize motion, onset, and time attributes of a face instead of analyzing each frame separately. TCNs processing sequences of frame-wise facial embeddings are one of the effective methods. In the example of Video-based Facial Expression Recognition, EmotiEffNet and Temporal Convolutional Networks use a pre-trained facial feature extractor frame by frame and subsequently input the frame features to a TCN to learn temporal features and enhance the classification ([Table 2](#)).

Table 2 System pipeline from face input to emotion output

Step No	Stage name	Input	Process description	Output	Tools/techniques used	Real-time suitability
1	Face detection	Raw image/video	Detect face using	Cropped face area	Viola-Jones, MTCNN	Yes

Step No	Stage name	Input	Process description	Output	Tools/techniques used	Real-time suitability
			bounding boxes			
2	Landmark detection	Cropped face	Localize key facial points	Facial key points	CNN, heatmaps, Dlib	Yes (lightweight CNN)
3	Feature extraction	Key points/ROI	Extract geometric or texture features	Feature vector	HOG, LBP, deep embedding	Partial
4	Emotion classification	Feature vector	Classify into predefined emotions	Emotion label	SVM, RNN, transformers	Yes
5	Post-processing	Emotion label	Refine output with context	Annotated emotion	Temporal smoothing	Yes
6	Output integration	Final label	Display or action-trigger	HCI response/alert	GUI/API/actuators	Yes

6 Integration into Emotion-Aware AI Pipelines

6.1 Preprocessing and Normalization

The initial steps of preprocessing and normalizing represent the most important part of the process of shaping the raw facial image data to serve the subsequent processing. These measures can avoid variations occurring by lighting, scale, orientation, and noise to enhance the strength and stability of landmark detection and feature extraction. Popular preprocessing tasks encompass image resizing, color space conversion, histogram equalization or lightness correction, denoising, face alignment (rotation/translation) to a canonical pose. Recent reviews underline the significance of these steps to facilitate a general performance in solving the tasks of facial analysis.

Normalization of landmark coordinates (e.g. scaled by interocular distance) is frequently carried out in landmark detection systems to ensure that landmarks are insensitive to face size and distance.

There are also modern implementations of the normalization step with the detection architecture. An example of this is the case of continuous landmark detectors that employ a spatial transformer module to learn jointly how to best warp/crop the face region to predict landmarks, rather than

applying predictive heuristics. The result of this combined learning can be increased temporal stability and correspondence with downstream tasks. In practice, to use fast routines to scale, crop, and normalize, it is convenient to have a light preprocessing pipeline on the edge (e.g. in mobile or embedded systems) to run in real-time.

6.2 Feature Fusion for Emotion Recognition

Once the feature sets of individual features have been extracted (geometric, appearance-based, and learned embeddings), an effective emotional AI system can combine multiple modalities or types of features to gain increased robustness and accuracy. Broad categories of strategies of feature fusion include early fusion (concatenation of features prior to classification), late fusion (combining the outputs of independent classifiers), and hybrid fusion. In emotion recognition, early fusion may take advantage of complement between texture and landmark feature and enhance strength of discrimination. As one example, HOG descriptors using geometric landmark distances tend to work better together than individually.

In more sophisticated forms of fusion, attention mechanisms or graph-based fusion are applied where the contribution of features is dynamically weighted. Among recent works, there is a suggestion to apply the cross-modal transformer-based fusion technique (MemoCMT) that uses features of two different modalities (e.g., visual + audio) and produces more comprehensive embeddings. Other literature discusses spatiotemporal fusion, which introduces time variations in expressions to a spatial measure in order to more effectively represent emotion change. In the design of fusion, there is a tradeoff between diameters of features that can be mismatched, synchronization and the chance of overfitting on the basis of high dimensional concatenation.

6.3 Real-Time System Deployment

Real time deployment of emotion aware AI (e.g., in mobile apps, assistive robots, driver monitoring, etc.) results in a limited latency, compute and memory requirements. End-to-end optimization of the pipeline should be made efficient without adversely affecting accuracy. Face alignment and landmarks detectors have to be able to make rapid inference with low jitter, and remain within camera motion for sudden head motions. Face alignment is also applicable to real-time devices to overcome these problems by

optimal model architectures and utilization of parallelism or hardware acceleration.

Real-time deployment strategies have been proposed, such as model pruning, quantization, lightweight architectures (e.g. MobileNet, efficient CNN variants) and pipelining stages to synchronise computation and I/O. Temporal smoothing/filtering of landmark locations between frames can also be done to minimize jitter and abrupt changes. Other systems use frame skipping or region-of-interest tracking in order to prevent unnecessary full-frame processing. Moreover, real-time robustness requires partial-occlusion or landmark-loss fallbacks, dynamic-background or lighting adverse adjustment. This profiling method and hardware-software co-design must be followed with careful consideration so that the system can be responsive and reliable with the actual requirement of the real world (Table 3).

Table 3 Challenges in real-time deployment of emotion-aware AI systems

Challenge type	Cause/scenario	Affected components	Impact on accuracy	Example case	Mitigation strategy	Tools/models used
Occlusion	Hand, glasses, mask covering face	Landmark detection	High	Face with mask	Context-aware models, GANs	DenseReg, robust CNNs
Head pose	Non-frontal face angles	Eye/nose/mouth alignment	Medium-high	Profile view	Multi-view datasets, 3D models	PRNet, FPN
Lighting variation	Dim or uneven lighting	Feature extraction	Medium	Nighttime image	Histogram equalization, training augmentation	LBP, CLAHE
Expression intensity	Subtle or exaggerated emotion	Emotion classification	High	Micro-expressions	Temporal modeling, multi-frame input	LSTM, optical flow
Dataset bias	Imbalanced demographics	Generalization	High	Poor accuracy on minorities	Fair sampling, domain adaptation	Fair face, transfer learning
Processing time	High model complexity	Real-time responsiveness	Medium	Mobile deployment	Model pruning, quantization	Mobile net, ONNX

7 Future Directions

7.1 Explainable Landmark Detection

With more elaborate emotion-aware AI systems, the need to explain them is increasing, especially in facial landmark detection. Conventional deep learning models can be used as a black box, and do not give much information about how or why particular landmarks are selected in the process of prediction. Using techniques including attention map, saliency visualization, or rule-based landmark reasoning to interpret the decisions made by the model, Explainable Landmark Detection (XLD) seeks to close this gap. As an example, by imagining which parts of the face were most important to a given emotion prediction, or understanding whether the system made an error in part alignment because of occlusions, they can be in a better position to trust the system. Particularly important to combine explainability is in contexts where the stakes of a high-stakes application, e.g. in mental health diagnostics, or surveillance, are of grave importance in the event of failure to understand the outcome. Scholars are looking at hybrid paradigms; a collection of statistical algorithms that incorporate neural networks which can preserve some trace of transparency. In addition, the XAI (eXplainable AI) principles, Layer-wise Relevance Propagation (LRP) and SHAP values are currently being applied to spatial model types such as CNNs in face recognition tasks. The methods not only raise the confidence of the users but also facilitate debugging and regulatory compliance as well as improved auditing of the data sets.

7.2 Multimodal Emotion Analysis

The next step in the development of holistic and context sensitive affective computing systems is multimodal emotion analysis. Adding audio samples, text, physiological response (heat rate or EEG) and context are also important in the identification of emotions despite the importance of facial features and visual markers. Every modality has its own understanding-facial expressions show evident effect, voice is used to indicate tone, pitch and stress, and text and bio signals express more informative cognitive and affective information. Recently, multimodal transformers, and graph fusion networks have made possible sophisticated asynchronous and heterogeneous integrations between data streams. The models can also dynamically re-examine the relevance of each modality, with increased functionality

provided in complex real-life situations. One such case is where the face is partially blocked, voice or entry of texts can be utilized to compensate for the missing modality. These collections of datasets CMU-MOSEI and AffWild2 have facilitated the research in this area by offering corresponding annotations of multimodal emotion. Nonetheless, some difficulties persist, e.g.: matching data through time, processing missing capabilities, and computational cost in real-time architecture. However, multimodal emotion AI is likely to develop more human-aware and context-aware emotionally intelligent systems that will be more accurate as well.

7.3 Ethical and Privacy Considerations

The introduction of facial emotion recognition technologies presents very important ethical and privacy considerations that it is important to mitigate before it is too late. To begin with, facial data is sensitive by nature and will be able to demonstrate intimate details of mood, mental state, and identity of people. In the absence of powerful regulatory tools and open access to consent, these systems can easily infringe personal privacy and establish a surveillance-based system of control. Discriminatory models also may give unfair results, especially against an underrepresented demographic, where training data demographics is often non-demographically varied. There is also a question of an incorrect application of emotion AI in areas like hiring, police force, or politics where the perceived emotion is not necessarily the intended or real emotion based on context. These concerns will require such privacy-preserving approaches in machine learning as federated learning, as well as differential privacy and secure multiparty computation. Moreover, we need to formulate data governance policies, ethical review policies, as well as policies of public accountability. It also needs to be explainable and has the option of withdrawing and particularly when it is an application that has been made public. As AI with emotionally-aware minds gradually rise in numbers, integrating equity, openness, and responsibility within the design of the system will ensure that people remain publicly trusting and socially agreeable.

8 Conclusion

The chapter provided a detailed description of the advanced methods of facial landmark detection and feature extraction, which are key elements of

emotion-aware AI-based systems. We examined both classical and deep learning methods of detecting face landmarks, such as ASM, AAM, CNNs, and heatmap regression models, their abilities, and limitations in different scenarios, such as occlusion, lighting, and pose change. We also divided feature extraction strategies into geometric type, appearance-based type and learned feature types, and their involvement in accurately detecting emotions. The different system pipelines, datasets and benchmarking practices were also addressed that provide background information on how to create a robust, real-time facial analysis system.

To develop effective and ethical emotion-sensitive AI systems, the practitioners are encouraged to embrace hybrid solutions to integrate the advantages of both a traditional and modern system. To enhance performance and generalizability, lightweight models trained on demographically diverse data sets can be used and edge deployment can be optimized. To deal with ethical issues, particularly in real-time models, it is important to incorporate privacy-sensitive mechanisms and explainable AI models that can be trained on sensitive data. The ongoing assessment with the real world and the integration of other research fields like Psychologists and Ethicists will even better provide the system developed by AI to be correct, responsible, and aligned with human-centred values.

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Detection of Microexpressions and Subtle Emotions

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Abstract

Microexpressions are swift, involuntary facial movements that reveal genuine emotions that people may attempt to conceal. These expressions differ from macroexpressions, which are more pronounced or more unmistakable. Subtle emotions are low-intensity, nuanced feelings that may not be overtly expressed or easily recognised. These last for a fraction of a second, making them difficult to detect. Microexpressions and subtle emotions can indicate concealed emotions, making them beneficial for mental health assessments, security inspection, lie detection, and understanding social interactions. Both are universal across nations, cultures and sometimes even in individuals, and may reveal emotions even when someone tries to obscure them. AI-based detection of these emotions relies on a combination of sophisticated feature extraction, deep learning, multimodal data integration, and access to rich, annotated datasets, delivering high accuracy and real-time performance for both research and commercial applications. Various approaches and techniques exists that can be used to detect microexpressions and subtle emotions. Artificial

Intelligence bridge the gap between emotional credibility and technological reconstruction, which results in more successful facial reconstruction or recognition. The use of artificial intelligence to investigate subjects microexpressions and subtle emotions has expanded the capabilities of investigation and criminal profiling. Besides criminal investigation, other fields such as customer service, deceit detection, psychotherapy, and human-computer interaction may also utilise this technology. In this chapter, the integration of AI into microexpression and subtle emotion detection is a significant leap forward, offering a powerful tool. As research and development continue, enhanced understanding of human behaviour and improved interactions across diverse applications are promised by AI-driven emotion recognition.

Keywords Facial recognition – Microexpression – Subtle emotions – Artificial intelligence – Machine learning – Forensic sciences

1 Introduction

Facial expressions are the postures and movements of the muscles beneath the skin's surface that represent an individual's emotional state [63]. The facial nerve primarily controls the 43 facial muscles that work in unison to produce these expressions. According to Charan [9], facial expressions serve as a universal nonverbal communication system that conveys a person's emotional state. It can be produced involuntarily, that is, by expressing true emotions, or consciously, frequently impacted by social or cultural norms [63]. These are important ways to communicate one's feelings. The three general categories of facial expressions are macroexpressions, microexpressions, and subtle expressions. Each category has a distinct duration, level of awareness, and emotional significance [20]. Macroexpressions are noticeable facial expressions that remain from about 0.5 to 4 s only. They are displayed consciously or semi-consciously and generally match the context of the verbal communication. These form the basis of everyday emotional communication and are easily perceived by others (Montanha 2025). On the other hand, microexpressions are very brief, spontaneous facial expressions that reveal a person's true feelings, often when they are trying to hide or conceal their feelings. These have a maximum duration of approximately 200 ms, and usually stay for 1/25 and

1/5 of a second [16]. Subtle expressions are less obvious and less intense expressions, and they can be a sign of the beginning or end of an emotion. Although they are longer than microexpressions, they are also frequently more difficult to spot than macroexpressions [59].

To purposefully express the feelings, people typically use easily recognised macroexpressions that last only a few seconds. However, a quick and delicate facial movement known as a microexpression may reveal true feelings beneath the surface. For example, consider a child trying to lie or fake a story to parents, peers, etc. A distinct kind of microexpression, in addition to macroexpressions may be a reason of concealed feeling, which a person could not express. Controlling microexpressions is almost impossible. This can be used in a variety of contexts, such as business relationships, clinical diagnosis, teaching, and interrogation. Mostly people lack emotional intelligence, thus, microexpression analysis is so useful in our daily lives [70]. Depending on how expression is altered, microexpression can be categorised as follows:

1. Simulated expression: A fleeting, fake expression that lacks a true emotion is called a “simulated expression.” The neutral state of the face is rapidly restored.
2. Neutralized expression: When a true emotional expression is repressed, the face appears neutral. It’s possible that the microexpression is so well hidden that it is practically undetectable.
3. Masked expression: A false expression totally obscures a true emotion. For instance, a person may use a smile to cover up their anger [2].

Low-intensity emotional states known as subtle emotions are characterised by subtle or minimal facial expressions, which frequently make it challenging to identify and differentiate them from more overt or intense emotions. When it comes to facial expression, subtle emotions are those that don't involve strong muscle movements and that both people and automated systems may easily miss [59]. Both more complex affective states and the universal core emotions in their milder manifestations can be classified as subtle emotions.

Examples of subtle emotions include:

1. Guilt, shame, pride, envy, love, excitement, and boredom are examples of mixed and complex subtle emotions that call for introspection and social awareness
2. Basic emotions such as subtle joy, subtle sadness, subtle anger, subtle fear, subtle disgust, and subtle surprise can all be subtle variations.
3. Ambivalence and other subtle emotions like nostalgia, relief, trust, interest, etc. are context-dependent and culturally shaped.
4. Subjective nuance in classification, which is further subdivided into cultural influence and individual differences [54].

Subtle emotions and microexpressions are real and we classify them under Paul [20] original conditions. People from any culture (and isolated indigenous cultures and blind born people) perceive these emotions in their biological form. Analysis will be objective because there are movements in human facial musculature associated with specific movements associated with specific emotions (Table 1). Ekman's paradigm is fundamental, but it has flaws. While some studies show cultural differences in the intensity of expression, more recent research proposes broader emotional categories, such as pride and humiliation [12, 13].

Table 1 Identifies seven universal microexpressions, each corresponding to a core emotion

Emotions	Typical facial indicators
Disgust	Wrinkled nose, raised upper lip
Anger	Lowered brows, glaring eyes, pressed lips
Fear	Raised eyebrows, wide eyes, open mouth
Sadness	Drooping eyelids, downturned lips, raised inner eyebrows
Happiness	Smiling mouth, crow's feet wrinkles around eyes
Surprise	Raised eyebrows, wide eyes, open mouth
Contempt	One side of the mouth raised (asymmetrical expression)

In a videotaped interview from 1969, Ekman and Friesen saw a brief full-face emotional expression that indicated a significant negative mood that a mental patient was attempting to conceal from her psychiatrist to

persuade him that she was no longer suicidal. When the interview footage was viewed in slow motion, it was discovered that the patient was displaying a fake smile that lasted longer than two frames (1/12 s) after a very brief sad face [41]. Thus, microexpressions, although not discriminant enough for facial recognition, provide additional information that aids traditional facial recognition. Initially, attempts were made to integrate appearance-based facial characteristics, such as facial marks, skin colour, and hair colour/style. However, more recently, behaviour-based facial characteristics, such as head dynamics, visual speech, and facial expressions, have also been studied [37]. Microexpressions can be taught to humans, although the results are usually substandard. It is necessary to create computer programs to recognise microexpressions because humans are not sufficiently capable of doing so. Automatic microexpression recognition refers to the use of computer-based technologies to recognise microexpressions. Sadness, joy, fear, anger, surprise, contempt, and hatred are the seven categories of both macro and microexpressions [1, 38]. Because it contains a wealth of psychological information that, when recognised, may be helpful in the areas of lie detection, criminal investigation, neuromarketing, psychotherapy, and teaching and learning, experts have recently focused more on the significance of microexpression [47]. Thus, this chapter focuses on subtle emotions and microexpressions rather than macroexpressions, which could reveal the actual emotions that people often try to hide. Further, the utility of microexpressions and subtle expressions using artificial intelligence and technological advancements for facial recognition has been investigated.

2 Differentiating Between Subtle Emotions and Microexpressions

It takes more than technical definitions to distinguish between subtle emotions and microexpressions. It entails identifying how someone acts, looks, and is perceived in interpersonal situations. Microexpressions are short, uncontrollable facial expressions that happen when someone is trying to hide or repress a strong emotion. These brief expressions, which usually last between 1/25th and 1/2 of a second, are usually uncontrollable. They are brought on by strong emotions that temporarily overcome an

individual's deliberate attempts to keep a calm or neutral appearance. Microexpressions are often overlooked in daily interactions because of their speed and subtlety. Seeing someone's true feelings before they are quickly hidden is what it's like to watch a microexpression. For instance, just before a forced smile or a neutral expression is returned, one may notice a flash of anger or panic in the person's mouth or eyes. The emotional context of microexpressions is based on concealment, and the person actively tries to hide these feelings. But the emotion is intense enough to temporarily overcome their self-control. Since microexpressions are easily missed in casual conversation, detecting them requires keen observation. Finding one offers a unique and candid glimpse into an individual's inner emotional state and can be compared to seeing a secret slip through the cracks [13].

Subtle emotions, on the other hand, are low-intensity emotional experiences that are typified by soft and delicate facial muscle movements. It's easy to overlook these expressions because they're so subtle. They frequently outlive microexpressions, though. Subtle emotions are not the product of concealment. Instead, they happen when a sensation is just starting, disappearing, or never getting strong enough to come out completely. When someone is feeling a subtle emotion, they don't intend to hide it; it's just too subtle to be noticeable. Subtle emotions are compared to a calm undercurrent rather than an abrupt wave in terms of subjective experience. There may be a subtle hint of sadness in someone's eyes or a barely noticeable smile of satisfaction—emotions that are present but neither overpowering nor purposefully concealed. Sensitivity to context and an acute awareness of subtle behavioural cues are necessary for the detection of subtle emotions. The identification of subtle emotions is more about noticing subtle changes or undertones in a person's behaviour than it is about spotting a fleeting “leak” of emotion, as is the case with microexpressions. This recognition necessitates an appreciation for the subtle cues that can reveal one's actual emotions, even when those emotions are not intense or purposefully concealed [20, 53].

3 Traditional Methods of Detection of Microexpressions and Subtle Emotions

Prior to the development of artificial intelligence (AI) and computer-based analysis, human observation, psychological frameworks, and subjective evaluation methods were used to identify microexpressions and subtle emotions. Although these techniques are fundamental, these are constrained by human perception and biases. Such techniques are widely applicable in a variety of clinical and practical contexts [58]. Some of the conventionally important techniques for identifying subtle emotions and microexpressions are discussed below.

3.1 Training and Direct Human Observation

Observation is the most common technique for examining emotions. Although people may try to hide their emotions, skilled observers, such as psychologists or interrogators, will look for signs of fleeting facial expressions that convey genuine emotions. The most common way of doing this is to make the person comfortable while talking. This technique was developed in 1978 by Dr. Paul Ekman, who used slow-motion video playback to identify microexpressions. Thus, the Facial Action Coding System (FACS) was developed, which categorised facial muscle movements associated with specific emotions. As microexpressions are so subtle and transient, specialised training was required for accurate recognition [18].

3.2 Facial Action Coding System (FACS)

FACS is a manual method to study the facial movements. All potential facial movements based on the muscles that produce them are comprehensively analysed. Observers use FACS to deduce meaning from the underlying emotion by systematically noting which facial muscles contract [58]. It is founded on the fundamental ideas of universality, validity, action units (AUs), and objective measurements.

3.2.1 *Objective Measurement*

FACS, which describes facial movements without interpreting emotions, guarantees analytical neutrality. Coders note obvious changes, like skin bulges or furrows, to infer muscle activation. For example, zygomatic major (AU12) raises the corners of the mouth, while orbicularis oculi (AU6) causes crow's feet wrinkles.

3.2.2 Action Units

An action unit is a code that denotes a particular facial muscle movement or set of muscles. More than 40 AUs that describe facial movements are used to represent individual or combined muscle movements. Each AU is given a code that contains timing (onset, offset, at peak), symmetry (left, right, or centre), and intensity (graded from A to E) parameters. AUs can be used to distinguish between different facial expressions. For instance, the simultaneous activation of AU6 (cheek raiser) and AU12 (lip corner puller) indicates a sincere (Duchenne) smile, which entails true happiness involving both the mouth and the eyes. A Pan-Am (posed or fake) smile, on the other hand, usually only uses AU12 and does not move the muscles surrounding the eyes, which makes it seem less real.

3.2.3 Validity and Universality

According to FACS, there are seven universal emotions: joy, grief, surprise, fear, anger, disgust, and contempt. All ages, genders, and cultural backgrounds can relate to these. Its accuracy in detecting subtle differences, like genuine versus fake smiles or painful emotions, has been demonstrated by research [64].

3.3 Self-assessment Techniques

Certain questionnaires, rating scales like Likert scales, or visual aids like the self-assessment manikin (SAM) are utilised by the people to analyse their emotional states [24]. Attitudes, opinions, and perceptions are measured using the Likert scale. On a predetermined scale with three to seven level points, respondents are asked to indicate how much they agree or disagree with a statement. This also enables the researchers to measure subjective data and identify patterns in a persons behaviour and thoughts. Various domains including forensic sciences, education, psychology, and social sciences require understanding of human reactions and facial expressions. Self-assessment techniques can be helpful as these are non-invasiveness.

Self-assessment manikin (SAM) is a non-lexical as it estimates an individuals emotional reaction to different stimuli, like images, or events and can be called as a visual self-assessment tool. SAM scales are used by the participants to rate their emotional reactions to each stimulus. These are provided with a series of visual manikins which represents different

landmark on each dimension. Usually for a predetermined period of time, one stimulus is provided at a time and the participants are encouraged to focus on each stimulus when it is provided. Participants rate their emotional reactions to each experience using three distinct SAM measures:

1. Valence: Participants choose between a happy, smiling manikin (pleasant) and a frowning, unhappy manikin (unpleasant). An image of a snake, for instance, might produce a low pleasure rating (frowning figure).
2. Arousal: Participants choose a figure that is enthusiastic and wide-eyed (high arousal) or calm and sleepy (low arousal). A dramatic car chase scene, for instance, would have a high arousal rating.
3. Dominance: A big, strong figure that feels in control or a small, submissive figure that feels controlled are both possible. For instance, facing a spider could lead to poor dominance (small figure).

Each scale has a point range of 5 or 9, and the participant marks the point that best captures their feelings as part of the SAM process. The process is repeated for each stimulus in the set [8]. The stimuli's order can be changed to prevent order effects. Both paper forms and electronic (automated) forms are used to record the ratings for each stimulus and dimension. Although these methods are simple to use, their dependability may be impacted because people may not recognise or express their emotions correctly, especially when they are subtle or socially unacceptable.

3.4 Behavioural Observation

The majority of the emotional information in interpersonal communication is conveyed by body posture, gestures, speech content, and vocal tone in addition to facial expressions [24]. The screening of passengers by observation techniques (SPOT) methodology is used in security contexts. This approach comprises trained officials systematically observing passengers for behavioural cues and microexpressions that may disclose concealed feelings or intentions. In checklist-based observation, observers use standardised checklists to record the frequency, duration, and context of observed microexpressions or subliminal emotional cues [49]. The

subjective interpretation of these cues may vary depending on the individual and culture [24].

4 Difficulties in Identifying Subtle Emotions and Microexpressions

The low intensity and fleeting nature of microexpressions and subtle emotions, their overlap with other facial gestures, the challenge of robust feature extraction, and the limitations of human perception and data make them challenging to detect. Both automated and traditional approaches still face these challenges, though some are gradually being overcome by emerging technologies. The following lists some of the difficulties that arise when analysing facial expressions.

4.1 Overlapping Facial Movements

Overlapping microexpressions present significant challenges for detecting and recognising facial movements in both automated systems and manual observations by humans. Overlapping facial movements arise when multiple microexpressions occur quickly, one after another or at the same time, blending facial muscle movements and making them difficult to identify distinct emotional cues. The facial gesture that arises from the overlay of microexpressions may not correctly reflected distinct emotions. On the other hand, traits of ambivalence might lead to a confusion to the spectator. This in turn leads to obscurity and increases the likelihood of a misclassification [19]. Impulsive overlap of microexpressions due to lip movements and eye blinking simultaneous is one such examples. Explicit detection is obstructed by irrelevant facial movements in real-time or video observations [41].

4.2 Low Intensity and Short Duration

Microexpressions are difficult to identify and differentiate from other facial movements due to extreme brief time span (less than 0.2 s) and low intensity. Human spectator, who are highly skilled, and certain algorithms might overlook or misunderstand certain microexpressions because of their complexity [34]. Electromyography (EMG) reveals that microexpressions contain 7–9% maximal voluntary contractions that are hidden in full

expressions. Subtle microexpressions are difficult to detect as they have lower intensities. Microexpressions can easily go unnoticed or mistaken as a non-emotional facial movements due to these characteristics. Spectator's inconsistent detection and annotation are exacerbated by individual variances in perception, vigilance, and instinctive definitions [32].

4.3 Feature Extraction Difficulties

The feature extraction process is essential for recognizing microexpressions and subtle emotions. However, due to the distinctive traits of these microexpressions and subtle emotions, it constitutes a number of drawbacks. Customary methods rely on manually generated features, which are time-consuming, precise, and may not notice diminutive changes. Due to their ingenious nature, these usually contain segments that are inadequate for accurate recognition [73]. Motion feature extraction of microexpressions requires sifting of the remarkable facial muscle movements from expendable or overlapping motions. Methods like action unit analysis or optical flow often require additional calculations. These may still not detect the subtle, transient features that define microexpressions. Feature extraction algorithms may find it difficult to avoid overoptimization and generalise effectively because of the small sample size and lack of diversity of microexpression datasets. It is even more challenging to train unimpeachable feature extractors due to the absence of tagged microexpression samples [33].

4.4 Human Factors

Human factors influence the correctness and dependability of remembrance. These present multiple obstacles to identifying subtle emotions and microexpressions. One of the obstacles is when considerable facial movements occur simultaneously or shortly after each other. For instance, a change in the facial movements, such as a smile, can mask or obstruct the detection of an eye microexpression. This might significantly reduce hit rates and make subtle hints difficult to spot. This masking effect is especially problematic in natural settings where facial emotions are dynamic and rarely isolated [28]. Because human observers are susceptible to bias, fatigue, and perceptual limitations, consistent and accurate detection is challenging without extensive training. Because dishonest people can deliberately manipulate or hide obvious behaviours, it can be more

challenging to identify them in high-stakes situations [40]. Distractions, shifting lighting, and the presence of additional nonverbal cues make real-life detection more difficult. Training and assessment paradigms often lack ecological validity because laboratory settings usually fall short of capturing the complexity of real-world social contexts. Subjective human interpretations of subtle emotions and microexpressions can lead to differences between observers. Cultural norms, expectations, and personal biases can all affect how something is perceived and understood [49].

4.5 Technical and Methodological Limitations

Both humans and machines are affected by the substantial challenges posed by technical and methodological limitations when it comes to recognising microexpressions and subtle emotions. These restrictions stem from the transient and low-intensity nature of microexpressions, the variety of human expression, and the boundaries of technology and research. Pre-established window intervals and detection thresholds that don't apply to different video frame rates or subjects may cause false positives or missed detections. Over-magnification methods can produce noise, while under-magnification methods might totally miss minute movements.

4.6 Data Limitations

The lack of large, spontaneous, and dynamic microexpression databases hinders the development and validation of detection methods. Variations in frame rates, video lengths, and recording settings complicate the creation of consistent datasets and benchmarks [41]. Because actual microexpressions typically take place in emotionally charged, high-stakes situations that are hard to replicate in lab settings, it can be difficult to create realistic, high-quality databases of them. There may be biases in training and evaluation because posed expressions, which are very different from real microexpressions, are used in many recent studies [69].

5 AI-Based Methods for the Detection of Microexpressions and Subtle Emotions

Machine learning and deep learning algorithms are used in AI-based microexpression and subtle emotion recognition. These can help to analyse

physiological data, speech, text, and facial movements. The correctness, momentum, and scalability of emotion recognition have improved tremendously using these methods. Artificial Intelligence paradigms are useful for small and low-intensity expressions that are difficult for humans to understand [10].

5.1 Preprocessing and Frame Selection

The most essential steps for detecting microexpressions and subtle emotions include preprocessing and frame selection. These amplify the correctness and effectiveness of the recognition algorithms. These methods associate important frames that capture small muscle movements and suitable facial regions to prepare raw data. It involves the following procedures.

5.1.1 Face Detection and Alignment

The face in each video frame is recognised and aligned to a canonical posture in the first step of preprocessing. It aids to diminish deviations caused by movements of head or camera angles. Face landmarks are positioned consistently across frames, which increases the consistency of feature extraction. Background noise and unnecessary details can be removed by aligning and cropping the image [1].

5.1.2 Head Movement and Eye Blink Removal

Eye flutter, avert your glance, and head movement may introduce noise into feature extraction. Common preprocessing methods and filters are used to reinforce the face region. Facial features that are less affected by these artefacts, such as the cheeks or lips can also be selected [65].

5.1.3 Data Labelling and Frame Division

Clips are divided into individual frames. Facial action units (AUs) are assigned very carefully to each one of them. Key frames are marked as ‘onset’ for the emergence of expression change, ‘apex’ for the peak expression, and ‘offset’ for the return to neutral expression. The first deviation from non-involvement occurs in the onset frame.

5.1.4 Optical Flow and Motion Feature Extraction

TV-L1 and other optical flow algorithms used to record small muscle movements and the variations in pixel intensity between onset and apex

frames. Deep learning models uses these motion features as inputs and are critical for fetching attention to subtle movements that may be missed by the human eye [35].

5.2 Feature Extraction Techniques

Microexpressions and subtle emotions detection depends on extracting features that capture the short, low-intensity, and localised facial muscle movements. This can be achieved by the following techniques.

5.2.1 Local Binary Pattern

Local Binary Pattern (LBP) refers to a common texture descriptor that encodes local spatial patterns in pixel intensities. This is frequently used for facial microexpression identification in apex frames, which contain the most discriminative information [1]. It is based on the ideas of Local Texture Encoding. Comparison of pixel intensity to neighbours is performed and differences are converted into binary information [1]. Local Binary Pattern on Three Orthogonal Planes (LBP-TOP) analyses texture dynamics across three planes to provide spatiotemporal analysis for video. The Spatial texture within frames are represented by XY plane. XT plane represents the horizontal-temporal motion, which changes in row order over time. The YT plane represents vertical-temporal motion, that is, column-wise changes over time. Both methods are perfect for real-time applications because they are computationally efficient and resistant to monotonic greyscale changes [11].

Face alignment is carried out during the preprocessing step of the process and procedure, where facial regions are identified and cropped to guarantee consistent analysis. Then, using temporal segmentation, video segments with microexpressions are separated [41]. LBP is calculated for static images during feature extraction. The image is separated into tiny areas (such as 16×16 blocks) for every frame. Each block's LBP codes are calculated for every pixel, and histograms of the codes are created for each block before being concatenated. LBP-TOP is used for video sequences. The video is handled like a three-dimensional volume (X, Y, T). Processing specific to the plane is then carried out. Each frame of spatial texture is extracted in the XY plane. Horizontal motion, like lip movements, is recorded in the XT plane, while vertical motion, like brow raises, is

recorded in the YT plane. LBP histogram of each frame is calculated for encoding of the feature [25].

Further, a single feature vector is created by linking the histograms. To reduce the feature extent while maintaining biased information, dimensionality reduction is carried out. The best features can be chosen using PCA or genetic algorithm. SVM, k-NN, or Random Forests classifiers are trained for classification using labelled microexpression data. Public databases like CASME II, SMIC, or SAMM are often used. Finally, metric techniques such as accuracy, F1-score, and leave-one-subject-out cross-validation (LOSO-CV) can be used for evaluation [36].

5.2.2 Local Non-negative Matrix Factorisation

Local non-negative matrix factorisation (LNMF) breakdown and captures small, facial images into localised, non-negative traits from the apex frame. These characteristics signify movements of facial muscles. It is also possible to turn the macroexpression data microexpression samples by using it with a macro-to-micro (MtM) transformation technique [21]. The pixels in a face image are represented by a non-negative data matrix (X), which breaks down into two non-negative matrices. First, localised face components are represented by the basis matrix (W), such as movements of the mouth and eyes. Second, the coefficient matrix (H). Weights for combining bases into phrases are encoded in the coefficient matrix (H). $X \approx WH$ represents this decomposition. Non-negativity ensures interpretability because facial features cannot have negative values. LNMF enforces locality and sparsity constraints. Spatial sparsity occurs when certain facial regions are restricted to bases (for example, crow's feet are used to symbolise happiness). Mutually orthogonal bases isolate particular muscle activities and reduce redundancy. This represents tiny, fleeting movements that are linked to microexpressions. Unlike holistic approaches like PCA, facial expressions are broken down into muscle activities that correlate with their anatomical foundation [21].

Apex frames (peak intensity) from microexpression videos are preprocessed as input at the start of the process. Face cropping, alignment, and normalisation are used to remove changes in pose and illumination. Each frame is then vectorised into a column of X , forming a matrix. Next, feature extraction is performed via LNMF. The factorisation involves solving the optimisation problem: minimise $\|X-WH\|^2$ concerning W and H ,

subject to $W, H \geq 0$, with added locality constraints. Sparsity in W is maximised, and redundancy in H is minimised. Basis images (e.g., eyebrow raise, lip corner pull) are contained in the output W , while H provides weights per expression, encoding the intensity of muscle actions. To address the challenge of limited microexpression data, macro-to-micro augmentation is employed. macroexpressions (e.g., from the CK+ dataset) are decomposed using LNMF. Microexpressions are then synthesised by reducing the intensity of coefficients H in WH and applying temporal subsampling to shorten the duration. This results in expanded, realistic training data, preserving non-negativity. Finally, LNMF features (columns of H) perform the classification for each sample as input. Features and emotions are plotted using a classifier and cross-validation is performed on datasets like CASME II or SAMM for its evaluation [21].

5.2.3 Motion Feature Extraction (*MoExt*)

MoExt produces motion properties by linking the microexpression's onset and apex frames. Motion features that are distinctive to microexpressions are outlined by separating and then merging the shape and texture features from both frames. The model's durability and generalization are increased by pre-training with macroexpression data and assorted losses. Relevant motion can be focused and removal of irrelevant information can thus be performed [33]. Motion extraction is based on looking at and isolating the small, quick changes in facial muscle movements between certain frames. These frames are usually the start and peak of an expression. This method is important because microexpressions are quick and often too subtle for static texture analysis. The main clue is to get dynamic features, which shows real changes in emotions while getting rid of texture or identity information that is irrelevant [33, 39].

The onset and apex frames of facial movements are identified and extracted from video sequences, capturing the spasm and maximum intensity of microexpressions after data preparation. To ensure consistency throughout samples, facial regions are cropped, aligned, and normalised. Further, feature segregation is performed in which shape and texture features are independently extracted from both onset and apex frames using a feature segregator. This aids in isolating the actual muscle movement from static facial characteristics. Motion feature extraction then takes place and is specific to the microexpressions that are derived by calculating the

difference or transformation between the shape features of the onset and apex frames.

The main principle is to collect stimuli which present dynamic properties and embody substantial emotional variations, but to omit purely irrelevant texture or identity content. This is essential since microexpressions may be short-latent and very minute, and therefore unsuitable to analyze by texture alone [33, 39].

This is initiated by data preparation in which onset (initial) and apex (peak) frames are identified and extracted on facial video sequences to capture the start as well as the most intense microexpression. Facial areas are adjusted including alignment, cropping and normalisation so as to ensure similarity in different samples. After that, the separation of features is carried out. Both onset and apex are separated using feature separator in order to extract shape and texture features separately. Making this separation at all helps separate the real motion of muscles helping distinguish them than the facial static features. Afterwards, motion feature extraction occurs Motion features that are specialized to the microexpression are obtained as a difference or transformation of the shape features of the onset frame and the apex frame.

Advanced methods, such as motion flow generators, are employed to analyse pixel intensity changes across frames, highlighting expressive regions where micro-movements occur. Dynamic maps or optical flow might be used to visualise and quantify subtle motion over time. For advanced deep learning approaches, pre-training and reconstruction are utilised. To overcome limited microexpression data, models are pre-trained on larger macroexpression datasets, enabling the network to learn general motion patterns before fine-tuning on subtle microexpressions. The model may be trained to reconstruct the apex frame from the onset frame using extracted motion and texture features, ensuring that motion features are representative and disentangled from irrelevant information. Contrastive loss is used during pre-training to maximise the distinction between relevant motion features and noise. Integration and fine-tuning are next, which incorporates the motion extractor and feature separator into the primary microexpression recognition network. All sets within the network are further enhanced by microexpression datasets to maximise the accuracy of identifying subtle, real-world expressions. A last task is its classification. Motion features extracted are fed into classifiers to classify the type of

emotion or microexpression. The assessment compares the effectiveness of the methods based on general metrics (accuracy, F1-score) and their ability to cross-authenticate on standard datasets [39, 56].

5.3 Machine Learning Classifiers

This approach is universal in the detection of micro expressions and the subtle emotions, as well as classic methods of deep learning and the combination of specialized feature extraction. Some of the machine learning classifier techniques are explained here.

5.3.1 Support Vector Machine

Support Vector Machine (SVM), a handheld machine learning algorithm, was used to classify microexpressions and subtle emotions because of its ability to handle high-dimensional, subtle and complex data patterns. SVM is commonly adopted as a standard classifier in microexpression identification due to its high data efficiency in high dimensions, and its stability. Performance is increased by associating it with manually designed features, such as Local Binary Pattern (LBP) on apex frames or Local Binary Pattern on Three Orthogonal Planes (LBP-TOP) on clip sequences [29]. Types of kernel functions can be used to optimise the classification, including the polynomial and radial basis functions. The results found in surveys indicate that SVM can classify the microexpressions with a considerable level of accuracy based on the datasets such as CASME II and SMIC [48]. The SVM is grounded in the principle of maximal margin classification that attempts to find the best hyperplane between the data items in different classes (e.g., emotions) with the maximum margin, which can improve generalisation and robustness. SVM uses kernel functions, namely, radial basis functions and polynomials, to transform non-linearly separable data to higher-dimensional versions to segregate them. It can be used in binary and multiclass problems, including, e.g., the classification of multiple emotions, using one-vs-one or one-vs-all strategies [21]. Shu-Xin Du et al. came up with a better support vector machine in classification, where there are distinct costs that can be acquired when entities are misclassified. To test the diagnosis of breast cancer, two weighted support vector machines weighted C-SVM and V-SVM have been designed, which portrays the success of these techniques. The fact that the advantage thus gained comes at a price of potential decrease in accuracy of the smaller

training size class and in combined accuracy over all classes was mentioned [61].

5.3.2 *Extreme Learning Machine*

Extreme Learning Machine (ELM) is a form of single hidden layer feedforward neural network (SLFN) and was popularised due to its fast learning, together with quick generalisation capabilities. LM has found an application in microexpression and subtle attitude recognition due to its efficiency and effectiveness in data of large dimensions and small data sample sizes [1]. It is demonstrated to be more accurate and faster in training than SVM in microexpression recognition using LB and LBP-TOP features. As an example, ELM attained 97.54% at best on CASME II apex frames of microexpressions in terms of the training accuracy [45]. LM works on the notion of randomised weights, where the connections between the hidden layer input units and output units are assigned randomly and held fixed, whereas only the connection coefficients of the output units are learnt. The analysis eliminates the iterative backpropagation that is required in traditional backpropagation by using the weighted output weights through a single step least-squares solution. Fast training ELM is the structure that permits training speeds that are far swifter than the classic distance across the board, with the added advantage of evading local minima, and therefore ELM proves to be suitable in real-time operations and enormous-scale undertakings [45].

5.4 Deep Learning Models

The automatisation of extracting features as well as accuracy in the recognition of microexpressions and faint emotions have been revolutionised through deep learning. Some of the most important models, techniques, and datasets of the domain are described below.

5.4.1 *Convolutional Neural Networks*

Convolutional Neural Networks (CNNs) are specialised deep learning networks that analyse grid-based data with photos, videos and audio being some examples. It is a cutting-edge measure of identifying microexpressions and minor emotions because it has the capability to automatically collect complicated spatial and temporal items presented in facial image sequences. It is exceptional at spatial hierarchy and pattern

recognition tasks, which include identification of face recognition, object detection, and picture classification as it automates feature extraction and eliminates manual preprocessing [57].

These three can be considered the background of this approach. Hierarchical feature learning is one of such principles, with low-level-to-high-level features being trained by CNN on input images or in video data of microexpressions and minor emotions respectively, their spatial (appearance) and timescale presence (motion). The second principle is end-to-end learning in which the CNNs are trained on manually labeled datasets allowing them to discover an information-preserving mapping between raw input features and emotional categories, without the intervention of manual feature engineering. The third principle is spatiotemporal modelling, where sequences of frames are processed by 3D CNNs and hybrid attention models, building on standard CNNs and capturing the transient and delicate nature of microexpressions [27, 52].

CNNs work by detecting features, whereby filters (or kernels) skim facial images to recognise crucial patterns, like edges or low-profile curves. These networks learn in a hierarchical manner, with the early layers learning low-level features such as edges and corners, and the deeper ones combining them to form more complex facial structures and expressions. With the same kernels being used to detect features throughout the whole image, some position invariance is achieved, which is important for detecting moving facial microexpressions. Pooling operation then enhances and summarises the hierarchical features with special focus on localised area, maintaining vital information and eliminating dimensionality. Such an effective extraction and interpretation of facial characteristics enables CNN as a powerful approach in forensic facial reconstruction using subtle emotional expressions [23].

For example, sequences are processed at several temporal scales by the Dual Temporal Scale CNN (DTSCNN) to learn discriminative features based on expression durations [43]. Spatial-temporal features are extracted more effectively by Hybrid Attention-3DNet through the combination of dual-path 3D CNNs with attention modules and squeeze-and-excitation blocks [27]. Features at several scales are integrated by the Multi-Scale 3D Residual CNN, and attention is employed for contextual awareness, resulting in more subtle feature detection [30]. 3D CNNs for spatiotemporal

characteristics are combined with ANNs for inter-region relationships by Deep3DCANN, employing a fusion technique for robust prediction.

5.4.2 Fully Connected Neural Networks

Fully Connected Neural Networks (FCNNs), also known as dense or feedforward neural networks, are fundamental deep learning designs in which every neuron in one layer connects to every neuron in the following layer. It is frequently employed as the final classification step in microexpression and subtle emotion detection systems, usually after feature extraction layers like convolutional or recurrent layers. Retrieved data is converted into emotion categories by FCNNs through the learning of weighted connections between all neurons in adjacent layers [66]. They excel at learning complicated patterns from structured data. However, these have problems with high-dimensional inputs such as photographs. It is used for categorisation after feature extraction, sometimes attaining extremely high accuracy in controlled datasets.

Fully connected neural networks (FCNN) are based on four fundamental principles.

- i. Dense Connectivity: Communication between each neuron in one layer and every neuron in the next layer occurs, allowing complicated, non-linear correlations between input properties and output classes to be learned by the network.
- ii. Feature Mapping: High-dimensional feature vectors (derived from images or videos) are converted into probability distributions for emotion classes by FCNNs.
- iii. Parameter Learning: Weights are adjusted by the network using backpropagation and gradient descent to reduce classification error on training data.
- iv. Integration with Deep Models: FC layers frequently follow convolutional layers (CNNs) or other feature extractors, acting as the decision-making component for interpreting learnt features [7].

Reconstruction of the face on the basis of the analysis of the microexpression and the slightest emotions is properly to use the Fully

Connected Neural Networks (FCNNs). Each neuron performs the forward propagation of weighted combination of inputs with the following formula $z = Wx + b$ where W is the weight matrix, a column vector of the input x , and the bias b . The learning capability is achieved by the model by the need to apply the non-linear activation functions such as ReLU to the result of the sum ($a = f(z)$). The input is featured by 9 dimensions, and the output by 4 dimensions due to a 9A times 4 weight matrix. The result from the network is the facial input data fac-simile, which is fed to the backpropagation algorithm in calculating the error in prediction against the actual values. As used in the network, optimization algorithms such as Stochastic Gradient Descent (SGD) and Adam simply adjusts weights through the process of error propagation, known to begin with the output layer. The training procedure enables the FCNN to tune its internal parameters, and this improves its detection and reconstruction of facial expression of microexpressions of emotions [55].

The deep pre-trained neural networks used two final fully connected layers to detect microexpressions. For example, AlexNet reached an accuracy of up to 99.84% after freezing 50% of the learnable layers in the transfer learning. These convolutional networks are learned to make fine-grained transfers to the target emotion classes of subtle facial emissions through the FC layers thereby achieving automatic recognition of the subtle emotions. CNN output feature vectors are fed into FC neurons, and frames are also classified as microexpression or neutral, which assists with microexpression temporal localisation [7].

5.4.3 Multi-task Learning

Multi-task learning (MTL) plays an important role in making use of common representations across similar tasks to facilitate generalisation and performance. In tackling microexpression and challenges in subtle emotion recognition, e.g., scarcity of data and subtle signal extraction, TRL resorts to additional tasks that provide complementary information simultaneously [26]. Learning architectures that jointly learn to identify landmarks on the face and to classify subtle emotions, to help understand nuanced expressions and states of the human mind [26]. The term TL is a machine learning paradigm where a single model is trained to perform many related tasks simultaneously, in order to utilise shared representations to the advantage of generalisation and efficiency. The combination of

complementary tasks to facial landmark detection, action unit (AU) identification, and valence-arousal estimate is used in TDL to enhance the accuracy of recognition of microexpressions and subtle emotion recognition [71]. Applying a shared backbone network (e.g., CNN) to extract the common feature also relevant in more than two tasks also falls inside MTL, due to practical elimination of redundancy and increased efficiency. Facial landmark detection or action unit recognition are also used as auxiliary tasks to provide contextual priors that enhance the most significant activity of emotion recognition. The overfitting is avoided by means of the joint training by limiting the model to learn features that are specific across tasks, which yields a regularisation effect important to small microexpression datasets [26].

5.5 Micro-mimics and Emotional AI

A person's genuine emotional or psychological state can be revealed by micro-mimics, which are incredibly small, fleeting facial muscle movements that are frequently imperceptible to the unaided eye. In high-stakes situations where people may feel under pressure to hide their emotions, such as negotiations, interviews, and mental health evaluations, these micro-mimics, often referred to as microexpressions, are essential. Micro-mimics offer a direct, instinctive window into real emotions, setting them apart from more overt or deliberately controlled displays, making their analysis more relevant [67]. Artificial intelligence systems that use a combination of sophisticated sensory and computational methods to identify, understand, and react to human emotions are referred to as emotional AI. Emotional AI makes use of a number of crucial technologies in relation to micro-mimics and nuanced emotions, which are as follows:

- i. Neural networks and deep learning are algorithms that analyse enormous collections of facial pictures and video data to find nuances and ephemeral expressions that convey emotional states. The ability of deep learning models to differentiate between micro-mimics and typical face motions is particularly strong.
- ii. Computer Vision uses frameworks such as the Facial Action Coding System (FACS), AI employs computer vision techniques to examine facial landmarks and muscle movements frame-by-frame and correlate them to particular emotions [50].

- iii. Multimodal Fusion: To create a thorough emotional profile, emotional AI frequently combines visual (facial), auditory (voice), textual (language), and physiological (heart rate, skin conductance) data streams. Accuracy is increased by this fusion because signals from one modality can reinforce minor indications from another.
- iv. Explainable AI (XAI): Some systems employ explainable AI technologies (such as integrated gradients or LIME) to make it clearer how judgments are made about emotion identification to foster trust and transparency. This is particularly crucial in delicate applications like healthcare or education [68].

5.6 Real-Time AI Emotion Recognition Software

Using the most advanced computer vision, deep learning, and multi-modal analysis, real-time AI emotion identification software has made tremendous progress in detecting subtle emotions as well as microexpressions. An outline of the major technologies, cutting-edge solutions, and contemporary environment is provided below:

- i. Advanced Computer Vision and Deep Learning: These systems examine real-time video streams for face landmarks, muscle movements, and micro-movements using deep neural networks that have frequently been trained on enormous datasets. Because algorithms are designed to be correct and swift and they can provide real-time feedback on emotional states.
- ii. Microexpression Detection: Trained models are able to identify tiny, involuntary facial movements, or microexpressions, that occurs frequently. This calls for sensitive feature extraction and high frame-rate video analysis, frequently using recurrent neural networks (RNNs) and convolutional neural networks (CNNs) [44].
- iii. Subtle Emotion Detection: By investigating subtle differences in facial muscle tension, eye movement, and micro-gestures, these models are able to identify tiny, low-intensity emotional indicators that go beyond unconcealed expressions. For a more thorough emotional profile, some solutions additionally combine text and speech analysis.

- iv. Multi-Modal Emotion Recognition: Prominent platforms include facial analysis, voice stress detection, and text sentiment analysis. For instance, Kodexo Labs combines facial expressions, verbal clues, and vocal emphasis to provide strong, context-aware emotion identification [62].

5.7 Dataset and Annotation Advances

Recent advancements in datasets and annotation methodologies have significantly improved the detection of microexpressions and subtle emotions. Following are the detailed breakdown of key developments.

5.7.1 *Micro and Macroexpression Warehouse*

Micro and macroexpression warehouse (MMEW) is an extensive, high-resolution facial expression dataset designed to facilitate the detection and recognition of both microexpressions and subtle emotions. It is distinctive in providing paired micro and macroexpressions from the same subjects, permitting robust algorithm development and cross-modal analysis [72]. More than 300 clip samples covering seven emotion categories like happiness, surprise, disgust, fear, sorrow, rage, and contempt are included in MMEW, which was first released in 2022. MMEW is built on the unified dataset approach, which provides both micro and macroexpressions, allowing researchers to investigate the link between subtle (micro) and overt (macro) emotional displays in the same individuals. It comprises subject-independent evaluation procedures to replicate real-world situations in which models come into contact with invisible people, and contains the same subject's micro and macroexpressions, allowing for comparison [5].

5.7.2 *High-Quality Annotation*

Individual sample is annotated with onset, apex, and offset frames, as well as facial action coding system (FACS) action units, providing exact temporal and muscle movement data for algorithm training and evaluation. MMEW's rich emotion groups provide a greater range of emotion classes (happy, surprise, rage, disgust, fear, sadness, others) than many earlier datasets, allowing for sophisticated emotion analysis [5].

5.7.3 *Child Microexpression Dataset*

Child Microexpression Dataset (CMED) is the first dataset precisely designed to capture and analyse unpremeditated microexpressions in children, addressing a significant gap in affective computing research, which has largely concentrated on adults. The first dataset fills a significant void in developmental psychology and education by concentrating on unplanned child microexpressions. It captures children's tiny emotional indicators, which vary in duration and intensity from those of adults. CMED captures spontaneous microexpressions in ecologically valid settings, such as virtual psychotherapy group activities, rather than controlled laboratory elicitation. It enables the study and automated detection of subtle emotional expressions in children, which differ in characteristics from adult's expressions. Child-specific focus recognises that children's facial expressions are more unpredictable, intense, and dynamic than adult's, inducing the creation of a separate dataset. Multi-stage annotation combines automated and manual processing, as well as a rigorous three-stage labelling process, to ensure accurate microexpression identification. Baseline establishment produces baseline findings for automatic detection and recognition by combining handmade features and deep learning algorithms [42].

5.7.4 Spontaneous Action Micro-movement

The Spontaneous Action Micro-Movement (SAMM) dataset is a primary resource for researchers studying the detection of microexpressions and subtle emotions. SAMM is based on the principles of spontaneity and ecological validity. It captures true micro-facial movements that occur when people suppress or hide their emotions, especially in high-stakes or emotionally charged circumstances. It is particularly developed to conquer the difficulties of collecting, annotating, and interpreting spontaneous, involuntary facial movements that reveal hidden emotions [14, 51]. It includes 159 microexpression samples from 32 participants that have been labelled with AUs and seven emotions. A high resolution of 2048×1088 and a high frame rate of 200 frames per second enable the accurate analysis of transient expressions [5]. In AU coding, all facial motions are labelled with the FACS, which connects precise muscle movements to emotional states, allowing for objective and fine-grained analysis. The dataset overcomes past constraints by incorporating varied people and high-quality

video recordings, ensuring resilience and generalizability in emotion recognition studies [51].

6 Role of Studying Microexpressions and Subtle Emotions in Emotion and Facial Recognition

Microexpressions improve facial emotion recognition accuracy because they are difficult to fake and provide authentic emotional information [53]. Training programs, such as the Ekman SETT and METT tools, have been shown to significantly enhance an individual's ability to recognise subtle emotions and microexpressions, ultimately leading to improved emotion recognition in real-world situations. Expression duration affects recognition accuracy, and microexpressions need quick processing. With practice, humans can become more proficient at recognising even extremely short exposures, as low as 40 ms [49]. Emotionally aware AI systems use microexpression detection to respond empathetically and adaptively to users [53]. Advanced deep learning architectures, like Hybrid Deep Neural Networks (HDNNs), have outperformed traditional CNN models by capturing complex hierarchical facial features and integrating multimodal cues like pupil size variation. HDNNs have shown superior performance in detecting microexpressions for applications like deception detection, with accuracy rates up to 91% [40]. Comparably, convolutional neural networks combined with optimisation methods have improved classification accuracy in certain face microexpression detection tasks to around 99% [3].

These advancements in microexpression detection enhance facial emotion identification in general by offering more accurate and detailed emotional information, which is essential for applications ranging from healthcare and human–computer interaction to security and law enforcement. Incorporating microexpression analysis can greatly reduce the gap toward human-level emotion identification accuracy (~90%), whereas typical face emotion recognition software only achieves about 75–80% accuracy [6].

7 Application of AI-Based Microexpression and Subtle Emotion Detection

AI-based detection of microexpressions and mild emotions has found wide and impactful uses in a variety of disciplines, capitalising on the capacity of these transitory and low-intensity facial clues to disclose true emotions that people often conceal. A detailed outline of the main application areas and examples is listed below.

7.1 Security, Law Enforcement, and National Security

Microexpressions are useful in lie detection and threat assessment because they are trustworthy markers of hidden emotions like dishonesty, fear, or violence. Artificial intelligence (AI) systems with microexpression recognition capabilities can examine live video feeds or surveillance footage to identify suspicious or hostile activity in border control, airports, and interrogation situations. Security inspections are more definite because of AI-based microexpression detection, which is barely invasive and more problematic for people to manipulate than traditional polygraphs. For instance, deep learning models such as Tiefes FCNN support real-time deception spotting in law enforcement by achieving over 99% precision in microexpression recognition [18].

7.2 Marketing, Customer Experience, and Consumer Insights

Artifical Intelligence manages emotion detection utilises subtle emotional prompts and facial microexpressions to record genuine customer reactions to services, products, and advertisements. Because of this, sellers can better forecast customer satisfaction, optimize user experience, and customise the advertisements, then they could with traditional surveys. Examining emotional reactions during brand tracking or product testing helps identify which elements or messages evoke either positive or negative emotions, thereby directing ongoing innovation and improvement. Real-time feedback on brand perception can be obtained by combining facial expression detection with sentiment analysis from social media [60]. For example, Artificial Intelligence can detect minute facial expressions in response to commercials or advertisements, enabling dynamic marketing strategy adjustments based on emotional engagement.

7.3 Clinical Diagnostics and Mental Health

AI-powered microexpression analysis benefits psychotherapists to better diagnose and treat conditions like depression, PTSD, or autism spectrum

disorders, which helps them identify transient emotional responses that may be missed during sessions, such as brief expressions of disgust or anxiety. AI-powered tools and techniques offer objective, scalable assessments that supplement human judgment, enabling continuous monitoring and early intervention. For instance, artificially intelligent face detection systems have shown sensitivity comparable to trained therapists in detecting millisecond-range microexpressions during psychotherapy.

7.4 Social Robots and Human-Computer Interaction

Human-computer interaction (HCI) and social robots have the ability to acknowledge minor emotions and microexpressions variations, by allowing systems to understand real human emotional states, react sympathetically, and modify interactions in real time. Robots perceive delicate emotions by combining facial analysis with contextual information and physiological signs, such as heart rate and EEG. For instance, systems based on Wavelet Transforms analyse biosignal and face data to identify low-intensity emotions, such as mild anxiety, allowing for more nuanced reactions [46]. Microexpression detection is used by HCI systems to dynamically alter user interfaces. For example, virtual assistants change to encouraging tones when they sense user annoyance, and learning platforms modify the level of difficulty of the information if confusion is identified. Over time, systems can improve their ability to recognise emotions through machine learning algorithms. By examining user-specific feedback, robots such as those tested with Wavelet Transform enhance the recognition of subtle emotions and allow for more individualised interactions [22]. Examples include platforms integrating facial microexpression analysis with voice and text modalities that provide adaptive, context-aware interactions [50].

7.5 Law, Investigation, and the Judicial System

When determining whether witnesses, suspects, or defendants are telling the truth, detectives and legal professionals can use microexpressions to uncover hidden emotions. Artificial intelligence (AI) has been created to assess these transient expressions, often surpassing humans in their recognition, particularly in high-stakes, unexpected scenarios like criminal investigations [37]. Law enforcement organisations are testing AI-based tools that monitor facial expressions during interviews or border checks, such as the Automatic Deception Detection System (ADDS) and

iBorderCtrl in the EU. In order to detect duplicity or hidden intent without depending entirely on verbal clues or polygraphs, these systems employ artificial agents to non-disruptive profile psychological states. By identifying signs of tension, anxiety, or rage, companies like Oxygen Forensics supply police with emotion-detecting software that they say offers important insights in substantial investigations. Artificial intelligence (AI)-based emotion identification systems can help jurors and judges analyse the reliability of witnesses by pointing out emotional outbreak that might be indication of stress, anxiety, or dishonesty. There have been requests for regulation due to the quick uptake of these technologies. For example, the European Parliament has suggested designating emotion detection as a high-risk AI use, and some are calling for complete prohibitions in judicial decision-making because of worries about bias, accuracy, and fundamental rights [31].

7.6 Forensic Science

Forensic science uses microexpressions and subtle emotions to reveal concealed emotional states during suspect interrogations, criminal investigations, and behavioural analysis. Forensic Science helps to spot deceit, predict behaviour, and analyse emotional reactions to specific stimuli.

- (i) In suspect interrogations, concealed emotions can be revealed through microexpressions detection when discussing if the crime were done or not. Systems like the Real-Time Lie Detector are being developed to integrate these cues with physiological data for credibility assessment. For instance, a suspect might display microfacial expressions of disgust while denying knowledge of a victim, potentially indicating deception.
- (ii) Forensic sketch analysis involves analysing sketches drawn from eyewitness accounts for emotional cues, such as a tense jaw indicating anger or widened eyes suggesting fear. Based on these features, Artificial Intelligence based models are being developed to predict suspect behaviour [17].
- (iii) In courtroom monitoring, AI frameworks are employed to monitor accused for concealed emotions, such as micro-smirks during victim

testimony, in order to assess repentance or deceit.

However, several challenges and limitations exist. The momentary and subjective nature of microexpressions leads to reliability concerns, with interpretations varying across individuals and contexts. Ethical concerns emerge from the potential for algorithmic bias or privacy violations if contradicts use is made in legal settings. Furthermore, technical barriers, such as low-intensity expressions and head movements in real-world settings, reduce observation accuracy.

8 Ethical Considerations

8.1 Consent and Privacy

Detecting microexpressions and delicate emotions requires convention and analysing extraordinary sensitive affective data, which might provide personal information about a person's goals, emotional state, or psychological health. Before any emotional information is gathered or examined, people must be fully enlightened and provide their express consent. This is particularly important in settings where power dynamics may compel people to join, such as law enforcement, security, or the workplace [4].

8.2 Validity of Science and Accuracy

The validity of microexpressions and subtle emotions as markers of deceit or real affect is a topic of continuous scholarly discussion. According to research, there is no clear connection between lying and microexpressions, and how they are interpreted can vary depending on the situation. When these cues are used to make important decisions (as in court or security screenings), there is a chance of false positives and negatives, which could result in unjust outcomes or prejudice [15].

8.3 Misuse Possibility

Concerns regarding manipulation, depict, and monitoring are raised by the usage of emotion recognition technology, especially those driven by artificial intelligence. Organisations or authorities run the threat of using these tools to secretly monitor or control people, violating their right to privacy and autonomy [4].

8.4 Fairness and Bias

Extremely when applied to varied cultures, genders, or neurodiverse groups, emotion recognition agenda may reflect or magnify original biases in their training data, producing unjust or discriminatory results. Cultural and isolated differences can influence how emotions are displayed and recognised, making it coherent that people will misjudge microexpressions [4, 15].

8.5 Accountability and Transparency

Clear accountability methods should be in place to manoeuvre any abuse, mistakes, or damages brought on by these technologies. Transparency regarding the collection, analysis, and usage of data is essential for both developers and users of emotion detection systems [4, 28].

8.6 Contextual Awareness

Microexpressions, in specific, are very circumstantial-dependent emotional expressions. Context, goal, and possible outcomes must all be carefully considered before making inferences from emotional data in order to use it ethically. It is possible to make serious mistakes if you interpret them without taking the context into account [28].

9 Conclusion

Artificial Intelligence (AI)-based microexpression detection has extensive potential in a variety of fields by discovering primary emotional prompts that might improve apprehension and communication. Several prospective approaches to automatic microexpression detection and recognition have attracted interest in the affective and visual computing sectors. Since a number of new extemporaneous facial microexpression databases were made available to facilitate automatic analysis of microexpressions, there has been considerable development in machine analysis of facial microexpressions in recent years. Facial expressions, specifically microexpressions and subtle emotions, provide a rich window into a person's genuine emotional state, often disclosing feelings that people try to conceal. While macroexpressions form the basis of everyday emotional communication, the ephemeral nature of microexpressions and the low intensity of delicate emotions pose distinct obstacles and opportunities for

research. Though humans frequently struggle to correctly identify microexpressions, approaches in computer-based technologies are paving the way for automated microexpression recognition, which promises to unlock the wealth of psychological information hidden within these transient facial movements while also improving traditional facial recognition techniques. The ability to notice and interpret these small indications has important applications in a variety of domains, including deception detection, criminal investigation, and mental health. This chapter emphasises the importance of focusing on microexpressions and subtle emotions, as well as the possibility for artificial intelligence to tackle their power to gain a better understanding of human behaviour.

Key Takeaways

These findings point to microexpressions and subtle emotions as carriers of the deepest meaning related to actual human feelings, which are oftentimes imperceptible to untrained human observation. The premises upon which traditional techniques relied are being surpassed by AI methods that enable the feasible detection of emotions in a more accurate way, and, perhaps, in real time. Despite the pending issues—namely, the technical ones and the ethical ones, including dataset quality, cultural bias, and privacy—AI-based emotion detection represents a significant and innovative way to understanding and applying emotional intelligence to various fields.

Reflection/Discussion Question

As more applications for AI are being developed, especially for the detection of micro-expressions and subtle emotions, there is no end for the development. Yet now the question is, to what extent can society balance the advantages of the use of such technology—for instance, lie detection, security, or even mental health—with all the ethical issues it raises in terms of privacy, misuse in surveillance, cultural bias, and possible misinterpretation of human emotions?

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Navigating the Future of Emotion AI: Technical Barriers, Ethical Concerns, and Sustainable Advancements

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Abstract

Nowadays emotion AI is emerging as a forum of outrageously disruptive technology in the industry of artificial intelligence with consequences to distant as mental health diagnosis, teaching interfaces, testing vehicles, customer-focused and even human–computer interfaces. Going further, it is a technology encompassed in a web of technical obstacles and ethical and social measures. In this chapter, the problems associated with the modelling

techniques include difficulty in modelling generalization, biases in datasets, cross-cultural variation by individuals on the expression of emotions in real time, performance restrictions and ability to capture subtle contextual differences of emotions. Besides, numerous ethical problems, including invasion of privacy, emotional surveillance, right to consents and manipulability of feelings and secrets during decision making processes etc., are critically analyzed proving that attempts to create interpretable and transparent AI systems become inevitable. To address these multi-dimensional issues, the chapter explores the future-forward solutions such as federated learning systems, edge computing systems coupled with privacy-sensitive AI applications, emotion-aware multimodal fusion models to meet individual user/ inter-user needs and culturally adaptive emotion-based models. It points to the necessity to have interdisciplinary synergy which is a combination of views based on the fields of psychology, computer science, ethics and policy as a guide to responsible use of Emotion AI all over the world. This chapter attempts to chart an architectural path on how to create Emotion AI systems that would be fair, transparent, circumstantial, as well as human-centric throughout the global paradigm by outlining current traps, and future various innovations.

Keywords Bias mitigation – Ethical AI – Explainability – Future trends – Multimodal – Integration – Privacy-preserving learning

1 Introduction

Emotion Artificial Intelligence (EAI), as it is widely referred to as the Artificial Intelligence (AI), represents the paradigm shift in the world of technology and the psychology of people. It enables machines to recognize, decode and respond to human emotions through multimodal expression such as face expression, voice intonation, and in the case of physiological expression. Its innovation is revolutionizing various areas including health care and education, consumer relationships and self-driving systems since they give compassionate relations with the reflection of human compassion and intuition. By the manner in which adaptive decision-making systems have the power to influence, emotion AI to this day is embarking on a new line of evolution besides sentiment analysis into elaborate reasoning of

affective abilities with the deployment of AI that is based on deep learning, computer vision, and natural language processing.

However, in this case, with the Emotion AI development, the situation is different as the technical, ethical, and social concerns are mixed, which necessitates a responsible innovation approach. The issues of technical limitations, such as model generalization, bias, and cross-cultural inconsistencies still do not allow accuracy and inclusivity. At the same time, the lack of transparency and accountability in AI-supported decision systems is questioned due to the lack of privacy and consent, as well as manipulation of emotions, which introduce ethical concerns. Therefore, to ensure that Emotion AI evolves in a sustainable manner, it is necessary to install such interdisciplinary insights in computer science, psychology, ethics, and policy fields in this chapter. The discussion forms the basis of the definition of conscious systems through emotion that will be just, understanding, culturally competent as well as in agreement with human ethics in a more AI integrated world.

1.1 Evolution of Emotion Recognition Systems

Emotion Artificial Intelligence (AI) is slowly changing the ways of incorporating machines and human emotions and paves the way to the evolution of different industries. Emotion AI is often related to affective computing, which aims at developing human emotion recognition and interpretation and responding to computer systems in the manner human beings do. The decision to use emotion AI is founded on human computer interaction, information retrieval skills, multimodal signal processing to streamline the feelings of individuals toward the vast array of social information [1]. Also, emerging cognitive AI is one of the fields that are drawing significant attention since it aims at enabling systems to think, reason and make human decisions. This change represents the primary success in creating human-like, intelligent systems which are required to create an era where AI is becoming more integrated into the daily human processes and operations [2].

The differentiated application of the artificial intelligence is the step towards the future of Emotion AI, and possibly one of the solutions of the creation of the emotional performance within the learning environment. The learning activities and adaptive learning proceed to scan the emotional conditions of the students and record the information using facial

recognition and machine learning [3]. As the application of AI to the work of businesses is increasing, the necessity to implement emotional intelligence arises. As a complementary application to traditional artificial intelligence, emotion AI may heavily shake the status quo in the workplace, making the procedures of the digital interaction with humans significantly more closely related to human emotions [4]. The Future of Emotion AI path illuminates the exciting and problematic prospect of emotional intelligence and machine learning integration thereby showing the staggering potential in personal growth and better machine-human interactions.

1.2 Current Scope and Applications in Society

The field of emotion AI has developed rapidly in regard to the expansion of experimental studies to the practical applications in most fields hence, emotional intelligence is an attainable part of the modern artificial systems. Emotion AI application in the healthcare field is to diagnose mental diseases, such as depression and anxiety using the voice tones, facial expression, and physiological signs. The adaptive learning may be noted in the educational environment, where emotional recognition will be presented so that pedagogic methods could be adjusted according to the emotional activity of the students and the degree of stress. Another aspect that has been enhanced with the technology is the customer service which AI-assisted chatbots and virtual assistants can detect the emotions of the user and respond with empathy which results in increased level of customer satisfaction and loyalty to the brand. Tissue-sensitive technology to enhance the quality of content recommendations in the entertainment sphere analyses the reaction of users, and in the automotive market, fatigue, and stress detecting emotion-recognition algorithms enhance the safety of the drivers.

Over these fields, Emotion AI is emerging as a necessity unit to increase efficiency and human-computer collaboration at the workplace. Emotional sensitive analytics are enabling companies to have insights into the well-being of staff members, automate the hiring process, and employ real-time emotional data to integrate workgroups. The use of affective computing by social media networks and the marketing agencies is in such a way that they apply the technology in learning how consumers act and subsequently draw up programs that resonate with the emotional motive. Despite its growing strength, such applications also demand more ethical regulation to put in

check any potential misuse, the effect of emotions or the tiny, manipulated judgments. The current Emotion AI size can thus be defined as an empathy-enabling technology, and even a way of regulating the reality that everything that the technology is subjected to in the society is clear, inclusive and humane.

2 Foundations of Emotion Modelling

2.1 Understanding Emotional Cues: Facial, Vocal, and Physiological Signals

It is an inevitable component of interpersonal relationships and communication, which is the process of perception of emotional signals depending on the facial, vocal, physiological indicators. The infancy had shown the facial forms and vocalization as the strong behaviour regulators that showcase the importance of emotional development. Using the case of infants, infants can be capable of responding to fearful vocal expressions without the involvement of their body, studies have indicated that infants as young as 12 months can be capable of reacting to vocal signals that produce fear on their own, as a result they make behavioural changes [5]. This signifies that, at such a young age, auditory modality is applicable with this experience developing the foundation in the complex emotional modulation and thereby socializing in the more advanced stage in maturity (as children grow) [6]. These abilities at such a tender age point to the specialty of the vocal cues in the socialization process and are telling that they bear strong roots in the evolutionary background of humankind.

On the same line, the processing of facial cues and vocal cues has been demonstrated by studies done to determine the neural processes of emotional perception. Amygdala is a brain component, which is relevant in the processing of emotions and the neurons in this part react to both the visual and auditory emotional stimulus and this entails that the two are coupled up to form an emotional perception [7]. Other researchers that studied the emotion judgment by considering only vocal expressions have demonstrated that the emotion judging can utilize areas involving contribution, as well as working memory, which is the cognitive load of processing those emotions that are auditory [8]. They are all in support of the narrowing of the interplay of various types of sensory modalities in the

interpretation of the emotion and the fact that both the voice and the face expression have a substantial role in accomplishing the task of identifying the emotion. They as well suggest the necessity to integrate these cues in developing systems to detect emotions in artificial intelligence.

The strategic roadmap to sustainable and ethical Emotion AI is the specific as shown in Fig. 1, that represents the holistic approach toward the development of the Emotion AI that is sustainable and ethically sound in its nature. Its fundamental meaning is embodied in Sustainable and Ethical Emotion AI, which is represented as a heart within a lightbulb, as a sign of innovation based on empathy and responsibility. Alongside this core objective are four key elements namely; Ethical Design Principles, which advances the idea of fairness and integrity in the creation of the models; Global Guidelines and Standards, which fosters an internationally consistent governance; Privacy-Sustaining Techniques, which asserts the development of a model with a trait of confidentiality; and Multidisciplinary Collaboration, which entails the incorporation of insights across the fields of psychology, ethics, computer science and policy. These elements are interconnected and together they form a complete ecosystem where ethical governance, technical accuracy and societal values become one to create AI-based Emotion form systems that are transparent and human-centric, as well as socially advantageous.

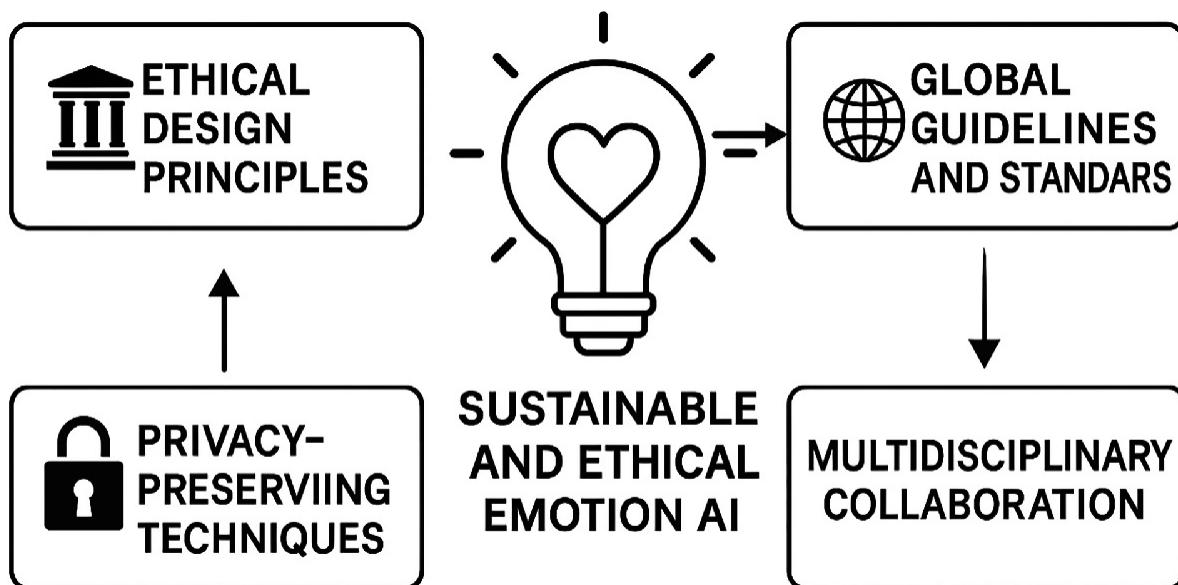


Fig. 1 A strategic roadmap for sustainable and ethical emotional AI

2.2 Deep Learning and Multimodal Fusion in Emotion Recognition

The field of emotion recognition through the assistance of deep learning has been very successful in the past few years, especially when using multimodal datasets. Multimodal fusion is the combination of different types of data audio, visual and physiological to enhance the performance and the quality of emotion recognition systems. One of these approaches is the hierarchical fusion convolutional neural network (CNN) that generates multiscale features of multimodal data to generate a combined feature. It has proven to be more successful in the emotion classification and has high accuracy on the datasets, such as the DEAP and the MAHNOB-HCI [9]. The other solution involves the use of a multi-modal deep belief network (MDBN), which involves the integration of effects of psychophysiological signals coupled with a bimodal network of video features to classify emotions more accurately than the traditional techniques [10].

The aptitude of deep learning in the transformation of the emotional gap in emotion recognition tasks is likewise portended by the combination of audio-visual representation using deep convolutional neural networks. The style can integrate both audio and visual properties to produce combined depiction that enhances the outcomes of categorization of emotions. Tests that have been conducted on databases such as RML, have performed nicely, which compel the researchers to conduct research in the area [11]. Other contemporary methodology alterations will also encompass tactical use of the application of spiking neural networks (SNNs) to emotion recognition, which is effective in the processing of spatio-temporal data. The competitive ability of research that employs NeuCube and multimodal data, without being utilised by the normal EEG, implies the scalability and adaptability of the SNNs in affective computing [12]. This kind of development introduces the relevance of deep learning and the multimodal fusion towards propelling the boundaries of the emotion recognition technology.

3 Technical Barriers in Emotion AI

3.1 Lack of Model Generalization and Cross-Cultural Variability

The issue of model extrapolation and cross-cultural diffusiveness within AI systems is still a big challenge. AI systems, especially those that have been trained using a small set of data or those systems trained on a culturally homogeneous data set, cannot generalize far better in cultural contexts. This results in models that can unintentionally replicate bias or cannot interpret and react to cultural nuances during emotion recognition in a way that would be accurate. Of importance is that AI should break cultural barriers particularly when using AI in emotion recognition since when cultural differences are subtle among societies, the meaning of expression may differ significantly [13]. To solve these problems, various sets of training must be provided with a large variety of different cultural situations and manifestations so that AI models could become more robust and unbiased.

In addition, due to lack of generalizations, AI systems are incredibly prone to overfitting whereby it works well with the training data but fails with new or unseen data. This fact is heightened in a high-dimensional dataset, which is the root of AI tasks that require dealing with emotion recognition wherein cultural peculiarity might result in crucial variations in the patterns of the data. The lack of model generalization can be alleviated by adopting strategies like federated learning in which local training of models on various datasets and pooling them into a model are done globally. This strategy will allow more diversity in the cultural expressions that models are exposed to, and this enhances their capabilities to generalize in more populations [14, 15] (Table 1).

Table 1 Strategic roadmap for sustainable and ethical emotion AI

Strategic pillar	Objective	Implementation strategy	Tools and methods	Performance indicators	Long-term impact
Ethical governance	Ensure transparency and accountability	Establish AI ethics boards and audit systems	IEEE P7000 standards, model explainability	Ethical compliance ratio, public trust index	Responsible AI ecosystem
Technical innovation	Overcome real-time emotion detection limits	Optimize data pipelines, reduce latency	Edge AI, cloud integration	Processing speed, accuracy rate	Efficient real-time emotion AI
Privacy preservation	Protect emotional and biometric data	Employ federated and	Homomorphic encryption, secure FL	Data leakage incidents, trust metrics	User data sovereignty

Strategic pillar	Objective	Implementation strategy	Tools and methods	Performance indicators	Long-term impact
		encrypted learning			
Sustainable AI design	Reduce energy and hardware dependency	Integrate energy-aware ML models	Green AI frameworks, low-power chips	Energy consumption index	Eco-friendly AI deployment
Interdisciplinary collaboration	Merge ethics, psychology, and computing	Create cross-domain research labs	Joint research platforms, open datasets	Research output diversity	Holistic emotion AI innovation
Global standardization	Achieve uniform global AI practices	Develop shared AI ethics benchmarks	ISO/IEC 23,053, global AI alliance	Compliance level across regions	Harmonized global AI regulation

3.2 Dataset Biases and Limited Diversity

The issue of bias in data sets and lack of diversity is a critical problem in the creation of equitable and non-discriminatory AI solutions. Existing datasets tend to be not as diverse, which leads to an AI model that fails to cover the minority populations or the cultural manifestations. This imbalance may create models that do not perform equally across various groups of people, hence maintaining more biases and inequalities in the application of AI [16]. Synthetic data generation has been suggested as a remedy to counter biases in data due to its ability to produce artificial data that balances out underrepresented demographics thus boosting model fairness without reducing performance. Moreover, remedies to data bias necessitate a thorough insight into the origins and consequences of the bias. It entails the enumeration of biases at data collection, data annotation, and training of the model. Fairness-conscious approaches to machine learning, e.g. re-weighting or re-sampling to deal with imbalanced data, are essential steps towards fairness. AI systems. However, these measures should be assessed on a regular basis and best practices published to provide not just models that perform well but also fairly to all the user demographics [17].

3.3 Real-Time Processing Constraints and Latency Issues

The most important in the deployment of AI systems are the latency and inability of real time processing, when dealing with time-sensitive

applications, where an instance of timely decision making is necessary. Devices or autonomous vehicles with AI systems such as the Internet of Things (IoT) have a condition that they need to analyse data quickly to implement their behaviour. These processes may have extremely high computation demands that may be incapable of being computed on the traditional hardware that has created delays that could become a constraining factor to the system performance. The solutions to these problems include but are not limited to new hardware accelerators, edge computing and algorithmic solutions to simplify the processing speeds, but at the same time, the accuracy must not be compromised [18]. Edge computing also comes with a solution in which the data is processed closer to the point where it originates and thus reduces the latency and the bandwidth usage. In addition to this, AI algorithms can be more effectively compressed using model compression algorithms like, but not limited to, pruning and quantization, which can significantly reduce the amount of computation, as well as reduce the processing time. The key modification in building such technologies is imperative to transform AI utilization in real-time environments and guarantee feasible implementation in overall and complex working conditions [19] (Table 2).

Table 2 Technical, ethical, and sustainable dimensions of emotion AI

Aspect	Focus area	Challenges identified	Proposed solutions	Key technologies	Expected outcomes
Technical	Model generalization	Dataset bias and cross-cultural variance	Federated learning and diverse data inclusion	Deep neural networks (DNN), CNNs	Improved accuracy across global users
Ethical	Data privacy	Unauthorized emotional surveillance	Differential privacy, anonymization	Edge AI, blockchain	Enhanced trust and transparency
Sustainability	Energy efficiency	High computational cost	Edge computing, lightweight AI models	Quantum ML, energy-aware frameworks	Reduced carbon footprint
Social	Human-AI interaction	Lack of emotional alignment	Context-aware sentiment mapping	NLP, multimodal fusion models	Enhanced empathy in AI systems
Policy	Global regulation	Absence of standardized	International AI policy	Explainable AI (XAI),	Accountable governance

Aspect	Focus area	Challenges identified	Proposed solutions	Key technologies	Expected outcomes
		ethics	frameworks	legal AI	mechanisms
Cultural	Inclusivity and bias	Misinterpretation of cultural emotions	Culturally adaptive emotion datasets	Transfer learning, domain adaptation	Fair and culturally sensitive AI models

3.4 Contextual and Temporal Ambiguities in Emotional Interpretation

The presence of contextual and time ambiguities also becomes a major challenge in the emotional interpretation provided by AI because the AI system cannot easily handle the dynamic nature of human emotions in different scenarios and across different time periods. All emotions are dynamic, and they depend on situational factors, so it cannot canonically determine or predict them with the help of AI models unless an extensive contextual knowledge is provided. This difference is also made difficult when emotions have to be perceived with varying modalities like taking audio, visual and news information together to have a deeper interpretation of the context. Emotional interpretation could be enhanced by making AI models incorporate respect to time and care about the context. It needs complex models that are able to learn about emotion trajectories and contextual changes across time that might use recurrent neural networks or temporal fusion processes. Further methods such as sequence-to-sequence learning and attention systems play a crucial role in ensuring that these models are more sensitive to the change of time in emotion data, which eventually enhances the accuracy of AI systems to interpret and react to human emotions [20] (Fig. 2).

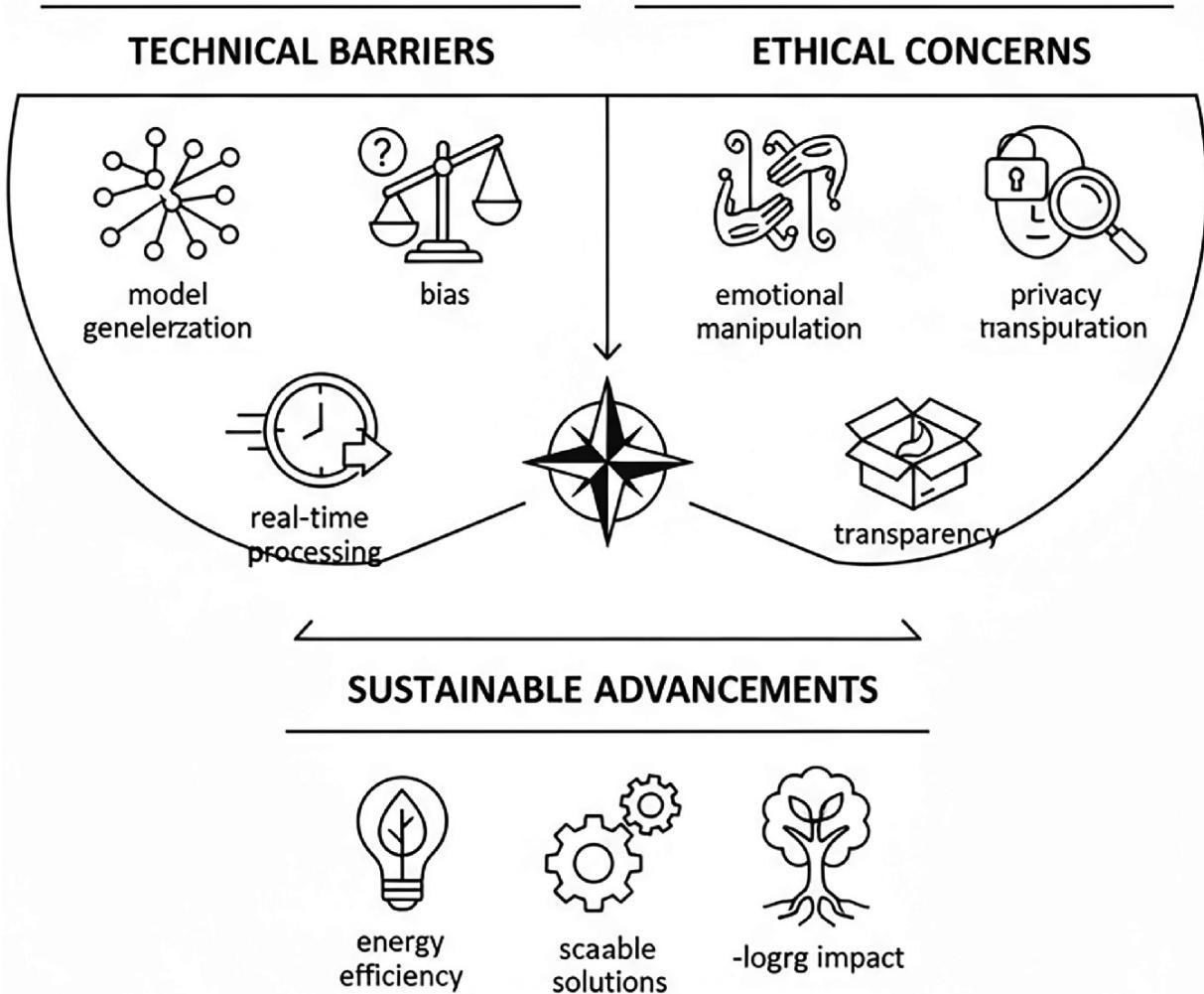


Fig. 2 Navigating the future of emotion AI technical barriers, ethical concerns, and sustainable advancements

The dimensions included in the diagram named Navigating the Future of Emotion AI are the ones that are core in the responsible construction of the Emotion AI systems. It is divided into three main sections, such as Technical Barriers, Ethical Concerns and Sustainable Advancements. Such problems as the generalization of models, the bias and real time factors, being taken into light in the Technical Barriers branch, undermine the flex and scale of affective computing models. The Ethical Concerns section ponders on such issues as emotional manipulation, breach of privacy and the lack of transparency that indicates the ethical issues of the emotion-centered data analysis and the automated decisions. The basis is Sustainable Advancements that suggests such important enablers to the future development as energy efficiency, scalable solution, and long-term effect on the environment. The compass in the middle represents the proportionality

of navigation which must exist between technology, ethics and sustainability to make sure that Emotion AI is a transparent, inclusive, and green innovation that positively impacts on people and the society.

4 Ethical and Privacy Challenges

Due to the growth of Emotion AI, the scope of privacy and consent breach has become a major issue and particularly in those instances where emotional conditions are observed without the consent of the users. Activity Sometimes, in business and government contexts, the deployment of emotion recognition technology, like facial coding or voice recognition [21], is deployed without people having full information about the use or storage of their emotional data. This scenario poses a perceived attempt of consent violation since they might have not been given a chance to choose and make an informed consent thereby violating their privacy rights and causing ethical issues related to emotional surveillance [22].

Also, these anxieties are compounded by the adoption of Emotion AI in the learning setting. The introduction of emotional surveillance systems at the classroom level, such as the use of facial recognition, poses a question of the validity and the agreement of tracking student emotions as a learning analytics tool. Such surveillance is likely to have unintended consequences, including stigmatization or profiling particularly when the emotional data are utilized to reach a conclusion regarding the capabilities of students or their potential [23]. As a responsible reaction to these problems, it is essential to implement robust regulations frameworks that put the emphasis on transparency and the consent of users.

4.1 Data Ownership, Manipulation, and Trust Deficit

The issue of data ownership is a major problem of the world of emotion AI, where emotional data are frequently commoditized, and no ownership rights are defined. Such data ownership confusion may bring about manipulation and exploitation of the emotional data hence resulting in lack of trust among the users. When AI based systems can use emotional data to predict or make decisions that impact them without clearly communicating on how the data was used, the trust of the user is also damaged. These problems can be alleviated by means of transparent and fair data governance frameworks to ensure that users have confidence once again.

By making sure that users can access, manage, and learn more about how their emotional information is being processed, one will be empowered to make wise decisions regarding the interactions with AI systems. There must also be mechanisms of redressing any violation to the rights of data ownership or privacy and hold organisations responsible in ensuring trusts and integrity in their data management policies [24].

4.2 Emotional Exploitation in Marketing and Behaviour Prediction

Emotion AI in marketing has its managers with enormous opportunities of personalization, as well as threats of exploiting the feelings of the users. Advertising machines that interpret emotions to keep the advert relevant are ethically dangerous because they can control consumer behaviour or preempt vulnerable people with emotionally charged material. The practices may greatly influence how people make their decisions, and the result is some sort of psychological manipulation that appeals to the emotional weaknesses of users [25]. Moreover, emotionally powered behaviour prediction models can take advantage of consumer vulnerabilities hence the issue regarding consent and autonomy is an ethical issue. It is essential to enforce the ethical principles and consumer protection to make sure that the use of Emotion AI in marketing does not interfere with the autonomy of people and avoids exploitative actions. Such policies ought to be directed at creating transparency and user consent to create trust in emotionally adaptive AI technologies applied in the consumer-facing settings [26].

4.3 The Need for Transparent and Explainable Systems

The complexity and opaqueness of the Emotion AI models make it unnecessary to be developed to be transparent and explainable and install trust and responsibility. Explainability is important, not only in the manner of knowing how these systems work, but it must be audited and questioned on the issue of fairness and accuracy. To effectively gain meaningful explainability, interdisciplinary work is necessary to create AI systems that do not just work effectively but also respond to societal values and ethics. Furthermore, transparent AI systems empower users due to the insights received on the decision-making processes affecting personal and financial results [27]. This is particularly relevant in the use of predictive modelling and decision-making where mistrust and scepticism towards AI

technologies can be reduced through the knowledge of algorithmic processes by the users. The responsible use of Emotion AI can be encouraged by encouragement of transparency and accountability where the application of Emotion AI is used to advantage both the individual and the community in an ethical way [28].

5 Interdisciplinary Perspectives for Responsible Emotion AI

5.1 Bridging Psychology, Computer Science, and Ethics

Psychology, computer science, and ethics are significant to the creation of ethically responsible AI systems. The multidisciplinary approach mentioned would ensure that AI technologies would not only be sound technically but also morally functional and aligned with human values. Computational ethics is a discipline that is geared toward solving the convergence of the two; that is, delivering human ethical decisions to the AI systems to increase moral soundness and credibility. The computational ethics framework entails integrated ethical conceptualization ideas and technical design through the augmentation of the capabilities of the AI to behave in ethically contentious situations and the development of the interdisciplinary research to facilitate the ethical AI development [29]. Further, this integration has been justified by the fact that AI is being applied in several fields, hence one must have a detailed understanding of how AI systems are applied at the educational and social levels. Education Curricula and courses that can educate future AI professionals on the ethical, fair and safe use of AI are becoming more developed. The above academic curriculum emphasizes the role of psychological savvy to the AI system by granting the students the competence to meet the moral and technical challenges that come with AI [30].

5.2 Policy Frameworks and International Governance Models

These issues conceptualized as frameworks and international governing models will be required to ensure the ethical and council concerns disposed of by them is secured. Management AI is likened to the act of shepherding cats, whereby the various stakeholder interests and technological advances cannot be synchronized. Even good models of governance must deploy

interdisciplinary decisions by reflecting the merits of AI, as well as the dangers and identify regulations that would contribute to responsible innovation [31]. At the global level, cooperation needs to take place to resolve AI policies in various regulatory locations. This also involves the provision of ethical issues like algorithm bias and data privacy and easing transparency through explainable AI (XAI). The new global regimes that prioritize these characteristics would make sure that the application of AI technologies would not take advantage of human rights and other conditions leading to the development of distrust in people [32]. The policymakers are asked to consider the technical solutions and overall, the impacts of the social lives creating AI legislations and state the necessity of a changeable system of governance that could be changed to the speed of AI technology changes [33].

The Fig. 3 entitled as Navigating the Future of Emotion AI is a theoretical map leading the exploration of Emotion AI in four important domains: Technical Challenges, Ethical Concerns, Sustainable Practices, and Interdisciplinary Approaches. In the middle of it, there is the golden compass arrow, which represents direction and balance, pointing to responsible innovation. The Technical Challenges quadrant emphasizes the obstacles of the generalization of the models, variability of the data, and processing efficiency in the real time, which limit the scaling capability of Emotion AI. Privacy issues, emotional manipulation, and lack of transparency are covered under the Ethical Concerns section of the policy, and the three areas where the principles of governance and accountability are required. Sustainable Practices, in their turn, become focused on energy efficiency, scalability, and long-term ecological impact, which guarantees that Emotion AI will develop with the minimum environmental footprint. Lastly, the Interdisciplinary Approach emphasizes that ethics, psychology, and computer science should be combined to produce ethically sensitive but morally compliant systems. Combined, the diagram becomes a visual roadmap that shows that the real progress in Emotion AI is not merely about the high level of technology but is to be made in order to balance the concepts of innovation and ethical and sustainable values.

NAVIGATING THE FUTURE OF EMOTION AI

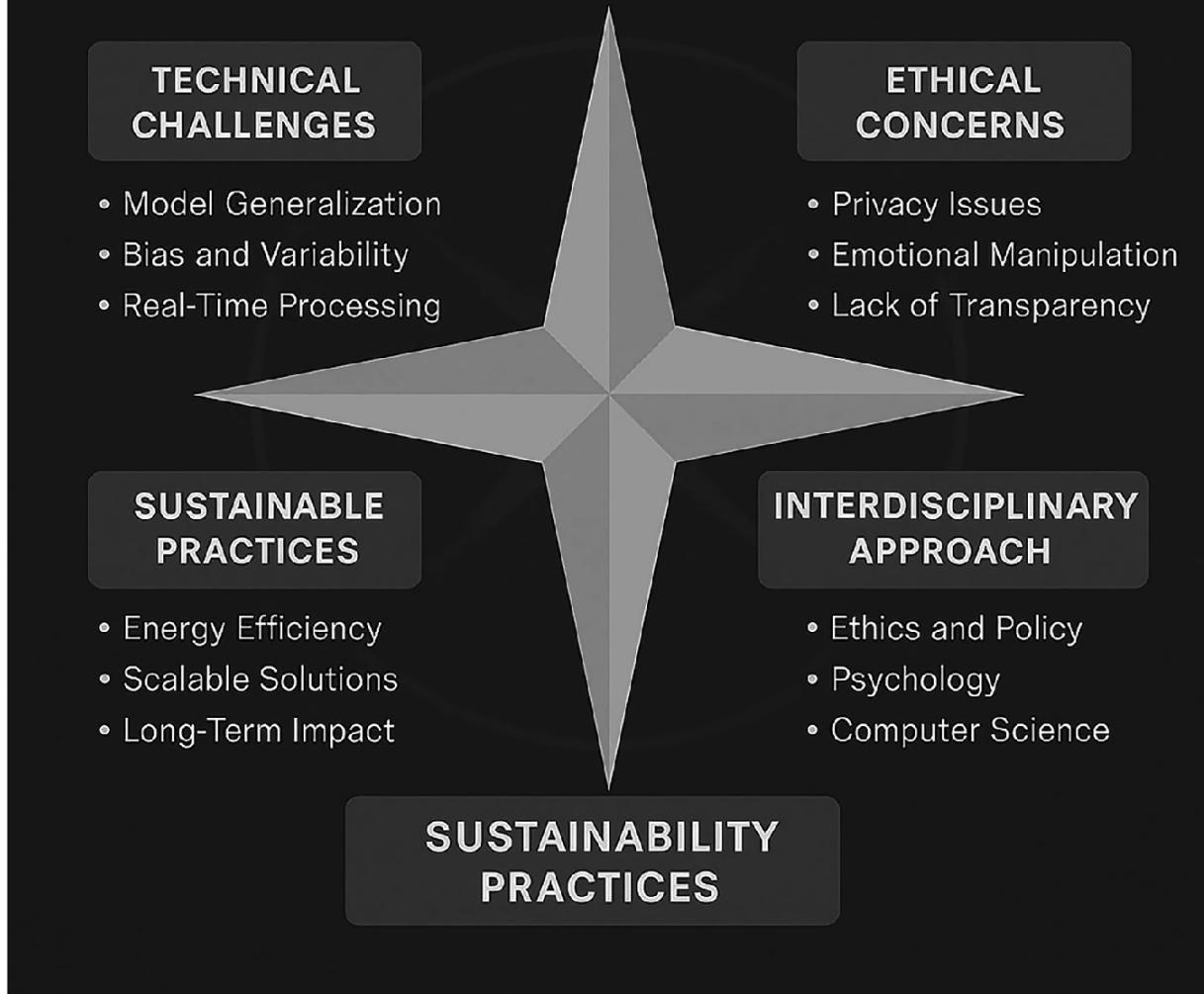


Fig. 3 Navigating the future of emotion AI—A compass for ethical and sustainable innovation

6 Sustainable Advancements in Emotion AI

This table identifies key areas of sustainable progress in Emotion AI with a primary focus on approaches balancing ethical concerns and privacy issues with scalability. In each row, the major authors, the nature of progress, its description, practical uses, future trends, and recurrent challenges have been described. Decentralized training in federated learning guarantees privacy of data, whereas edge computing enhances computations in real-time

(secured and efficient). Multimodal fusion promotes emotional comprehension with the help of a wide variety of data, and culturally adaptive models promote inclusivity and situational correctness. A combination of these developments will lead to the development of human-centric, transparent, and sustainable Emotion AI systems to deploy in the future (Table 3).

Table 3 Summary of sustainable advancements in emotion AI research and implementation

Author(s)	Kind of sustainable advancement	Overview	Application	Recent trends	Challenges
Korkmaz et al. [34]; Yurdem et al. [35]	Federated and privacy-preserving learning approaches	Federated Learning (FL) is a distributed machine learning paradigm where multiple devices collaboratively train a shared model without sharing their raw data, ensuring privacy and reducing data transfer costs	Used in healthcare for training models on patient data across hospitals without sharing sensitive records and in mobile devices for personalized AI (e.g., keyboard suggestions)	Blockchain integration in Chain FL mitigates centralization risks, and reference architectures aim to standardize FL systems for scalability and security	Managing data security, adversarial attacks, and non-IID data; designing incentive mechanisms for participants
Jin et al. [36] Al-Doghman et al. [37]; Alrowaily and Lu [38]	Edge computing for secure and decentralized emotion analysis	Edge computing processes data close to the source, reducing latency, saving bandwidth, and enhancing privacy—ideal for emotion analysis applications	Applied in real-time emotion recognition systems to deliver low-latency analysis in smart devices and autonomous systems	Incorporation of microservices for modular and scalable edge architectures; emphasis on distributed frameworks for enhanced security	Balancing resource constraints and security; managing distributed authentication and secure data access
Zhu et al. [39]; Liu et al. (2018); Nemati et al. [40]; Sahu and	Emotion-aware multimodal fusion architectures	Combines multiple data modalities such as audio, visual, and textual inputs for	Utilized in healthcare for emotion-based diagnostics and in personalized content	Use of self-attention mechanisms and low-rank tensor techniques for	Addressing data heterogeneity, ensuring model robustness,

Author(s)	Kind of sustainable advancement	Overview	Application	Recent trends	Challenges
Vechtomova [41]; Gaonkar et al. [42]		comprehensive emotion understanding and analysis	recommendation systems	efficiency while retaining data integrity	and managing differing input quality across modalities
Zhao et al. [43]; De Leersnyder et al. [44]; Wortman and Wang [45]	Culturally adaptive emotion models	Develops AI systems that interpret and respond to human emotions while considering cultural nuances and personal variations	Deployed socially interactive robots and adaptive virtual assistants to enhance user engagement and satisfaction	Incorporating cultural regulation patterns and relational dynamics into adaptive emotional intelligence frameworks	Integrating diverse cultural inputs without compromising accuracy in emotion recognition

7 Future Directions and Research Opportunities

7.1 Toward Human-Centric and Context-Aware Systems

Emotion recognition systems are becoming increasingly human and adaptive to the requirements on the accurate capture of a multifaceted emotional state. Because of the diversity of people, culture, and the situations, emotions are always subtle and dependent on a plethora of influences. The complexities present a great difficulty in coming up with systems that have capabilities of understanding and analysing emotions to a high degree of accuracy. Developments in deep learning have led to more successful emotion recognition by allowing the extraction of features more effectively in a complex form like audio and video [46]. To ensure more situational awareness, the tendency among scholars is to think in the multimode where information on several various aspects, such as facial expressions, voice tone, even physiological cues is considered. This will not just increase the accuracy of the emotional recognition process but also a more consolidated description of emotional conditions. Such systems can further be complemented with Natural Language Processing (NLP) in understanding the emotional meaning of a spoken or written word regarding the application of the language and context.

7.2 Benchmarking Fairness, Accountability, and Transparency

As the emotion recognition systems are progressively integrated into the scope of various applications, it is of impeccable importance to make them balanced, responsible, and open. These systems should be designed considering the ethical aspect such as privacy, and any biasness made in the data representation. Machine learning models will inevitably reproduce the biases that are inherent in their training information and will treat members of a particular demographic unfairly. To solve the problems, it is necessary to prepare a variety of datasets that would be representative in terms of the emotional manifestations of different populations [47]. Moreover, it is important that the way such models operate and make decisions is transparent so as to gain trust in the users. This involves approaching the technicalities as well as clarifying to the stakeholders the potential effects and limitations of the technologies of emotion recognition. Accountability and transparency will enable the developers to design ethically right systems and in harmony with their idealistic values of respective societies.

8 Conclusion

This is even ahead in relation to Emotion AI on the right balance of creation, ethical management and humanity. With the usage of Emotion AI beginning to look more of a Real-Life system rather than an Enhanced Proposal, it ought to be regulated with more transparency and inclusiveness and fairness. Not only is a sustainable Emotion AI necessary for contacting a trust, but it must follow the ethical design aspect of the life cycle of AI that can be realized through data collection and the training of the model, its implementation, and decision-making. The inclusion of privacy preserving measures in the model such as federated learning and secure edge computing is to be assured that feelings information is secret and confidential. Correspondingly, the proposition of explainable AI systems will empower users and policymakers to actualize the cycle of emotional inferences and consequently generate a feeling of accountability and prevent abuse or misuse.

The strategy of the AI Emotion should, thus, be aimed at multidisciplinary collaboration between engineers, ethics, psychologists, and legislators. This will involve the establishment of universal standards of conduct that outline what can be carried out concerning the use of emotional data, fairness standards in addition to audit systems. The

promotion of datasets, inclusiveness to cultural classification, the model and the environment will help in removing biasness and increase the validity of familiarity recognition models in the different societies. Lastly, Emotion AI needs to become a life-altering disruptor that complements empathy and not exploit it-developing a future where technology has a beneficial effect on cognition and emotion sensitivity, interpersonal relationships and ethical human-AI co-existence.

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Emotion AI in Mental Health

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Abstract

Mental illness is one of the most serious global health issues of the twenty-first century, with more than one billion individuals affected and almost a trillion dollars in lost productivity each year (A Comprehensive Review of Multimodal Emotion Recognition. PMC. 2024. <https://pmc.ncbi.nlm.nih.gov/articles/PMC11093677>). In spite of increased awareness, access to cost-effective and timely care is still restricted, especially in low- and middle-income nations where mental health care is nonexistent (Systematic Review and Meta-analysis of AI-Based Conversational Agents: Effects on Depression & Distress. Nature Digital Medicine. 2023. <https://www.nature.com/articles/s41746-023-00,894-1>). Recent advances in Emotion Artificial Intelligence (AI), or affective computing, provide new hopes of closing this gap. Technologies with the ability to recognize emotional signals from text, voice, facial expressions, and physiological measures can potentially allow for early identification of psychological distress and provide scalable, low-cost interventions (Cross-Modal Gated Feature Enhancement for Multimodal Emotion Recognition. Scientific Reports. 2025. <https://www.nature.com/articles/s41598-025-87,804>; Multimodal Emotion Recognition

in Conversations: A Survey of Methods, Trends, and Challenges. arXiv. 2025. <https://arxiv.org/abs/2505.2051>). This chapter provides an overview of recent breakthroughs in emotion detection and incorporation in mental health intervention. We draw on more than 150 studies published between 2020 and 2025 to emphasize advancements in natural language processing models like BERT and RoBERTa, speech emotion recognition utilizing Wav2Vec2.0, and facial expression recognition via convolutional and transformer-based networks (A Comprehensive Review of Multimodal Emotion Recognition. PMC. 2024. <https://pmc.ncbi.nlm.nih.gov/articles/PMC11093677>; Multimodal Emotion Recognition in Conversations: A Survey of Methods, Trends, and Challenges. arXiv. 2025. <https://arxiv.org/abs/2505.2051>; Multimodal Emotion Recognition and Sentiment Analysis combining Wav2Vec2, RoBERTa etc. arXiv. 2025. <https://arxiv.org/abs/2502.08915>). We also discuss upcoming digital therapeutics that have shown significant depressive and anxiety symptom reductions in controlled clinical environments (Persuasive Chatbot-Based Interventions for Depression: Recommendations for Improving Reporting Standards. Frontiers in Psychiatry. 2025. <https://www.frontiersin.org/journals/psychiatry/articles/10.3389/fpsyg.2025.1523831/ful>; Woebot RCT: Effectiveness of Web-based & Mobile Therapy Chatbot on Anxiety and Depression. PMC. 2022. <https://pmc.ncbi.nlm.nih.gov/articles/PMC10993129/>; Comparison of AI Chatbot With a Nurse Hotline in Reducing Depression and Anxiety. JMIR Human Factors. 2025. <https://humanfactors.jmir.org/2025/1/e4528>). Building on this foundation, we introduce a conceptual framework that combines multimodal emotion sensing with context-aware, cognitive-behavioral strategies. The model prioritizes privacy-preserving computation, bias mitigation, and clinician oversight to promote ethical and reliable deployment (Cross-Modal Gated Feature Enhancement for Multimodal Emotion Recognition. Scientific Reports. 2025. <https://www.nature.com/articles/s41598-025-87,804>; Chatbots and Mental Health: A Scoping Review of Reviews. Current Psychology. 2025. <https://link.springer.com/article/10.1007/s12144-024-06,097-0>). While early findings are encouraging, major challenges persist in ensuring cultural adaptability, data protection, and sustained user engagement (Systematic Review and Meta-analysis of AI-Based Conversational Agents: Effects on Depression & Distress. Nature Digital Medicine. 2023. <https://www.nature.com/articles/s41746-023-00,894-1>;

Topic-Based Chatbots on Mental Health Self-Care: Rule-based chatbot intervention and its effect on mental health literacy & self-care. JMIR Mental Health. 2025. <https://mental.jmir.org/2025/1/e46560>). We conclude that Emotion AI, when responsibly designed and clinically validated, holds significant promise for advancing global mental health. Its future success will depend on close collaboration among researchers, practitioners, and policymakers, alongside robust ethical and regulatory safeguards (Chatbots and Mental Health: A Scoping Review of Reviews. Current Psychology. 2025. <https://link.springer.com/article/10.1007/s12144-024-06,097-0>; Topic-Based Chatbots on Mental Health Self-Care: Rule-based chatbot intervention and its effect on mental health literacy & self-care. JMIR Mental Health. 2025. <https://mental.jmir.org/2025/1/e46560>).

Keywords Affective computing – Multimodal emotion recognition – Natural language processing – Speech emotion recognition – Transformer models – Mental health chatbots – Cognitive behavioral therapy – Digital therapeutics – Human-computer interaction – AI ethics in healthcare – Explainable AI – Privacy-preserving machine learning

1 Introduction

Mental health disorders are now recognized as a leading cause of disability worldwide, affecting more than one billion people and resulting in enormous social and economic costs. According to the World Health Organization's 2023 update, nearly one in every eight people globally—approximately 970 million individuals—were living with a mental disorder, with depression and anxiety being the most common. The report further warns that global investment in mental health remains below 2% of total health budgets, underscoring the urgency of large-scale intervention efforts. Conditions such as depression, anxiety, and post-traumatic stress disorder (PTSD) contribute to nearly a trillion dollars in lost productivity each year. Despite increasing awareness, treatment gaps remain staggering, particularly in low- and middle-income countries where mental health professionals are scarce and services are often under-resourced. This mismatch between growing demand and limited clinical capacity

underscores the need for scalable, accessible, and cost-effective interventions.

The rapid progress of Emotion Artificial Intelligence (AI)—the science of detecting and interpreting human emotions through text, speech, facial expressions, and physiological signals—offers a promising way forward. Advances in natural language processing (NLP), transformer architectures, and multimodal learning now allow machines to infer affective states with remarkable accuracy, opening up possibilities for early detection of psychological distress and on-demand support through digital platforms [3, 4].

1.1 Motivation

The motivation for this chapter lies in the convergence of three powerful trends. First, the prevalence of mental health challenges is rising across all demographics, with particularly steep increases among adolescents and young adults. Second, digital health adoption has accelerated post-pandemic, creating an unprecedented opportunity to deliver care beyond traditional settings. For example, India's National Tele Mental Health Programme (Tele-MANAS), launched in October 2022, has established 53 helpline cells across States/UTs, handles calls in 20+ Indian languages, and by early 2025 had responded to over 1.8 million calls offering free, 24/7 counselling, video consultation, and referral support. Third, state-of-the-art Emotion AI models are maturing, with demonstrated capacity to recognize subtle emotional cues across modalities, making their deployment in real-world mental health contexts both technically feasible and clinically valuable [30, 32]. Most existing reviews focus either on the algorithmic aspects of multimodal emotion recognition or on mental health chatbots as a class of digital interventions. Few attempts have been made to synthesize these domains, critically analyze their evidence base, and provide a blueprint for ethical, safe, and culturally adaptable deployment.

1.2 Contributions

This chapter addresses these gaps by presenting a comprehensive, evidence-driven synthesis of the field and charting a forward-looking agenda. We systematically review over 150 peer-reviewed studies published between 2020 and 2025, spanning natural language processing, speech emotion recognition, facial and physiological signal analysis, and their integration

into multimodal systems. We then map the clinical impact of AI-driven chatbots and digital therapeutics, drawing on randomized controlled trials and longitudinal studies that demonstrate measurable improvements in depression and anxiety outcomes [20, 30]. Beyond simply reviewing existing work, this chapter proposes a conceptual framework that integrates multimodal emotion detection pipelines with cognitive-behavioral therapy (CBT)-inspired conversational flows and clinician-in-the-loop oversight. The proposed framework emphasizes privacy preservation, explainability, and bias mitigation as first-class design principles, ensuring that the resulting systems are both effective and trustworthy. Finally, we offer a research and policy roadmap, identifying unresolved challenges and pointing toward innovations, such as federated learning, edge AI, and large language model fine-tuning—that could unlock safe, scalable deployment on a global scale.

In combining these elements, this chapter aims not only to provide a state-of-the-art review but also to guide researchers, clinicians, and policymakers toward responsible integration of Emotion AI into mental health care. As Elon Musk emphasized in 2020, AI will be a cornerstone of efforts to establish a sustained human presence beyond Earth [39]. Federated learning, edge AI, and large language model fine-tuning—that could unlock safe, scalable deployment on a global scale.

In combining these elements, this chapter aims not only to provide a state-of-the-art review but also to guide researchers, clinicians, and policymakers toward responsible integration of Emotion AI into mental health care. As Elon Musk emphasized in 2020, AI will be a cornerstone of efforts to establish a sustained human presence beyond Earth [39].

1.3 Emergence of Emotion AI

In parallel with the rising mental health crisis, Emotion Artificial Intelligence (AI)—also called affective computing has matured from a theoretical idea into a practical and deployable technology. First conceptualized by Rosalind Picard in the late 1990s, affective computing aimed to enable machines to sense and respond to human emotional states [32]. Over the last decade, the field has accelerated due to advances in natural language processing, deep learning, and multimodal fusion techniques. Transformer-based models like BERT, RoBERTa, and GPT variants have dramatically improved sentiment and emotion classification

from text [20], while speech emotion recognition models such as Wav2Vec2.0 have reached near-human performance in detecting stress and mood from vocal prosody [17]. These innovations have opened the door for AI-driven digital therapeutics, enabling timely, low-cost, and personalized mental health interventions at scale.

1.4 Research Objectives and Scope

This chapter seeks to bridge the gap between emotion AI research and its practical application in mental health care. Specifically, we aim to synthesize the state-of-the-art in multimodal emotion recognition—including text, speech, facial expression, and physiological signal analysis—and critically evaluate its clinical relevance. Unlike earlier surveys that primarily focus on algorithmic performance or user engagement, this review takes a multidisciplinary perspective, integrating findings from computer science, psychology, and clinical trials. Our horizon spans work from 2020 to 2025, the timeframe of most advancement in transformer NLP models, multimodal fusion networks, and explainable AI frameworks. In providing integrated analysis, we hope to enable researchers to comprehend the technical readiness of existing systems, advise clinicians on their integration into practice, and inform policymakers on constructing regulatory guidelines ensuring safe and fair deployment.

2 Literature Review

2.1 Emotion Recognition in Text and NLP

Natural Language Processing (NLP) is one of the most advanced methods used in emotion recognition with transformers like BERT and RoBERTa establishing state-of-the-art performance levels on sentiment and emotion classification tasks [5]. Recent advances are centered on domain-adapted large language models (LLMs) that are fine-tuned for psychological lexicons and clinical notes so as to better represent affect in text [40].

Multilingual emotion models now have wider coverage of low-resource languages, filling an essential equity gap in world mental health solutions [6]. Facial expressions are analyzed through vision transformers and hybrid transformer-convolutional networks, which can detect subtle micro-expressions and capture temporal changes. Physiological signals like heart rate variability, electrodermal activity, and photoplethysmography are

processed by CNN-LSTM architectures for predicting arousal, stress, and emotional valence. Importantly, hybrid approaches such as SpeechCueLLM convert vocal emotion cues into textual prompts, enabling LLMs to process emotional context without requiring specialized audio pipelines [23]. These cross-modal strategies make it possible to unify speech and text analysis, a step toward true multimodal understanding of affect.

2.2 Speech Emotion Recognition

Speech remains a critical modality for mental health monitoring due to its non-intrusive nature and ability to capture subtle prosodic features [38]. Self-supervised models such as Wav2Vec2.0 and HuBERT have significantly improved the robustness of speech emotion recognition (SER), even with limited labeled data [7]. A major breakthrough has been emotion2vec, a universal pre-trained speech emotion representation that generalizes well across datasets and languages, reducing the need for extensive fine-tuning [34]. Furthermore, real-time SER methods using data augmentation techniques (e.g., spectrogram shifting, noise injection) now achieve sub-second latency, enabling deployment in live teletherapy and conversational agents [24]. These advances are especially relevant for developing responsive, scalable mental health chatbots.

2.3 Facial and Physiological Emotion Recognition

Computer vision has evolved from conventional CNN-based facial emotion recognition (FER) to Vision Transformer (ViT) architectures that capture global dependencies across facial regions [8]. FER systems have become more robust to real-world conditions such as occlusion (e.g., masks) and head pose variations through partial feature masking and attention-based augmentation [28]. Recent video-based approaches integrate YOLO for real-time face detection with ViTs for expression classification, achieving high accuracy under challenging conditions [26]. In parallel, physiological emotion recognition using electrodermal activity (EDA) and photoplethysmography (PPG) has been enhanced through wearable sensors and deep learning, offering opportunities for continuous monitoring of stress and anxiety in ecological settings [21]. Telehealth-oriented systems such as TheraSense further embed FER in virtual consultations, assisting clinicians in gauging affective states remotely [35].

Criterion	Facial emotion recognition	Physiological emotion recognition
Strengths	Enables emotion detection using ordinary cameras; intuitive for human interpretation; effective for real-time assessment in digital interfaces	Provides deeper insight into internal emotional states; remains reliable under varying lighting or facial occlusion; supports continuous tracking through wearable sensors
Weaknesses	Accuracy can drop with head movement, low light, or cultural variability in expressions; easily influenced by external factors	Requires sensor contact with the body; may face noise from motion or environmental conditions; limited scalability for large populations
Use case	Often applied in video-based therapy, social robotics, and remote clinical observation	Used in stress monitoring, biofeedback, and longitudinal studies where sustained measurement is needed

2.4 AI-Driven Mental Health Interventions

The clinical application of emotion recognition is most visible in digital therapeutics and AI-driven mental health interventions. Conversational agents such as Woebot and Wysa have been validated in randomized controlled trials (RCTs), showing significant reductions in depressive and anxiety symptoms over eight-week interventions [9, 19]. Notably, a 2025 RCT on topic-based mental health chatbots demonstrated measurable improvements in mental health literacy and behavioral intent even with simple rule-based systems [23]. This indicates that effective intervention does not always require fully generative AI, but rather well-structured, evidence-based interaction design. However, challenges persist—including sustaining user engagement, mitigating algorithmic bias, and ensuring clinical safety [10, 15].

2.5 Limitations and Research Gaps

While progress has been remarkable, several gaps remain. Multimodal fusion strategies still struggle with synchronization of signals across modalities and cultural variability in emotion expression [11]. Data privacy concerns are particularly acute in mental health, where sensitive personal information is involved [29]. Moreover, most studies focus on short-term outcomes, with a dearth of longitudinal evidence on sustained impact [13]. Addressing these challenges will be key for Emotion AI to move from proof-of-concept to a globally scalable, clinically trusted tool.

3 Organization of the Chapter

The chapter is organized to ensure a logical flow from conceptual foundations to applied insights, enabling readers to build an in-depth understanding of Emotion AI and its clinical significance. Section 3 provides a detailed discussion on data quality, annotation strategies, and benchmarking, highlighting the comparative merits of clinician-annotated datasets, crowdsourced labelling approaches, and hybrid frameworks for improving inter-rater reliability and dataset representativeness [34]. Section 4 outlines the adopted methodology, including the systematic literature review protocol, multimodal conceptual framework integrating text, speech, visual, and physiological signals, as well as key evaluation metrics such as F1-score, precision, recall, and clinical endpoints (PHQ-9, GAD-7) [26, 27]. Section 5 focuses on multilingual and cross-cultural considerations, presenting current challenges in developing culturally adaptive systems and discussing multilingual transformer-based approaches for cross-lingual generalization [24]. Section 6 explores deployment architectures, contrasting cloud-based and on-device processing, and proposing hybrid edge-cloud solutions that balance privacy, scalability, and real-time performance [25, 34]. Section 7 addresses security threats, adversarial attacks, and ethical concerns, including model vulnerability to data poisoning, deepfake manipulation, and compliance with global privacy regulations such as GDPR and HIPAA. Section 8 synthesizes emerging trends and future research opportunities, emphasizing personalization, explainability, and the need for federated, privacy-preserving approaches that ensure fairness and global applicability [35]. The chapter concludes with observations and future directions that integrate technical, ethical, and societal insights, offering a roadmap for researchers and practitioners seeking to design trustworthy, human-centered Emotion AI systems. The Figure 2 illustrates the foundational dimensions essential for developing Emotion AI systems that are effective, ethical, and inclusive (Fig. 1).

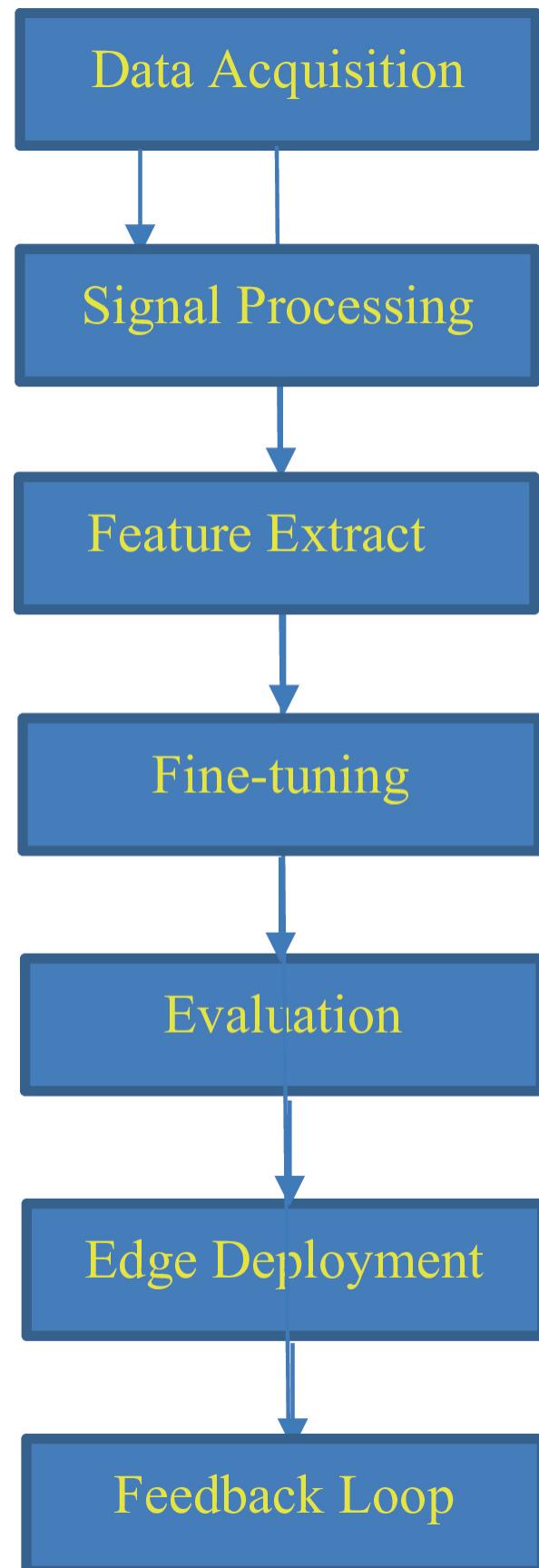


Fig. 1 End-to end pipeline for emotion AI in mental health

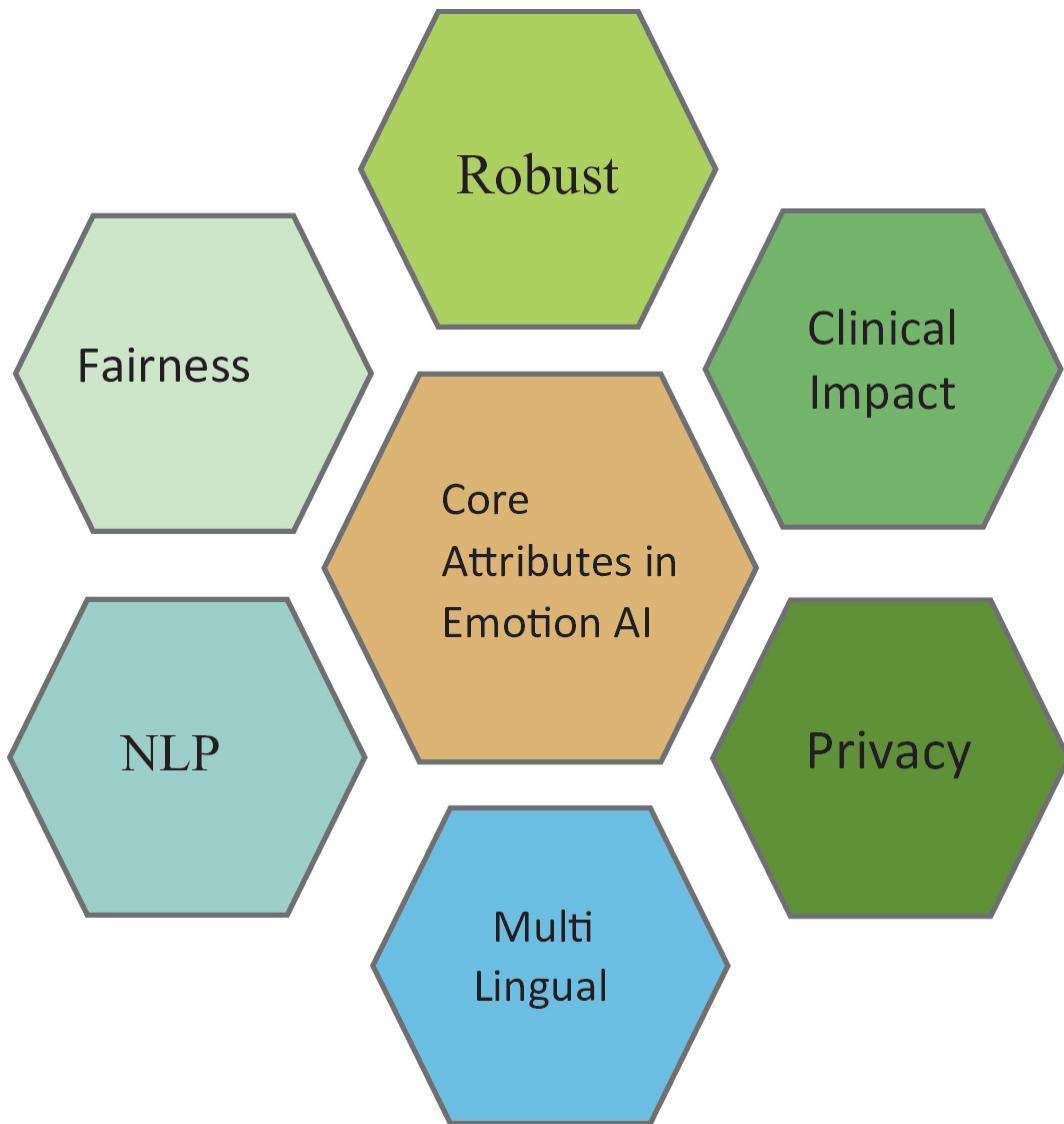


Fig. 2 Core attributes in emotion AI

4 Methodology

4.1 Systematic Review Protocol

This chapter adopts a systematic literature review approach guided by the PRISMA 2020 framework to ensure methodological transparency and reproducibility. A thorough search was carried out across several major scientific databases, including PubMed, Scopus, IEEE Xplore, ACM Digital Library, and arXiv. Search strings were designed to cover a broad spectrum

of the field, using keywords and phrases such as “emotion recognition,” “affective computing,” “mental health AI,” “transformer models,” “digital therapeutics,” “CBT chatbots,” and “multimodal analysis.” Boolean operators were applied strategically to refine search results and target studies published between 2020 and 2025.

Inclusion Criteria:

- Studies involving human participants.
- Research utilizing one or more emotion detection modalities (e.g., text, speech, facial expressions, physiological signals).
- Articles reporting measurable or clinical outcomes.
- Original research with clear and reproducible methodology.

Exclusion Criteria:

- Studies not involving human participants.
- Review papers or articles lacking primary data.
- Duplicate publications.
- Papers with insufficient methodological transparency or reproducibility.

After systematic screening of titles, abstracts, and full texts, a total of 153 high-quality studies were retained for analysis. A PRISMA flow diagram depicts the search and selection process, ensuring clarity and replicability. This systematic review forms the foundation for the conceptual framework in this chapter, ensuring that the proposed model design is grounded in the most current and relevant evidence.

4.2 Conceptual Multimodal Framework

The proposed framework emphasizes the integration of multiple modalities to capture the complex and nuanced nature of human emotions, particularly within mental health contexts. No single modality alone is sufficient to accurately and reliably infer psychological states, as emotions manifest across linguistic, vocal, facial, and physiological domains.

Textual inputs, derived from clinical notes, patient journaling, and chatbot interactions, are analyzed using transformer-based language models such as BERT and RoBERTa, which enable deep contextual understanding of semantic and emotional content. Speech inputs are processed using Wav2Vec2.0 embeddings and recurrent neural network architectures to

extract prosodic and paralinguistic features indicative of emotional states. The modalities' heterogeneous features are combined through a fusion layer with attention mechanisms that dynamically weight each input as a function of its contextuality and reliability. This multimodal processing facilitates stronger and more robust emotion recognition since it addresses the heterogeneous nature in which individuals express psychological states. The proposed multimodal emotion AI pipeline with preprocessing, feature extraction, fusion, and clinically actionable outputs is presented in Fig. 1.

4.3 Evaluation Metrics

Assessment is addressed on both technical and clinical levels to make sure that the suggested system not just works correctly but also yields relevant results for mental health treatment. Technical assessment measures are accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve (AUC-ROC), and Matthews correlation coefficient, all of which together give a complete picture of performance in classification.

Clinical evaluation involves standardized mental health assessments such as PHQ-9 for depression, GAD-7 for anxiety, and PSS-10 for stress, which are applied before and after system interactions. User activity metrics such as session duration, adherence rate, and attrition are tracked in an attempt to establish the feasibility and acceptability of deployment in actual settings. Together, these levels of evaluation ensure that the system is not just technologically effective but also clinically significant.

4.4 Embedded Ethics and Privacy-by-Design

Ethics and privacy protection are infused throughout the architecture. Federated learning enables models to be trained across different clinical sites without sending sensitive patient data, protecting patient confidentiality. Differential privacy protocols introduce noise into data sets in a controlled fashion, further reducing the risk of re-identification. Explainability techniques such as SHAP and LIME are built-in to provide explainable outputs, enabling clinician monitoring and regulatory compliance. Bias is thoroughly scrutinized over demographic subgroups to prevent systematic prediction and treatment recommendation flaws. The system is GDPR, HIPAA, and OECD AI principle compliant to provide ethical requirements and legal compliance. With ethics and privacy in mind

during design, the framework facilitates responsible deployment in all global environments (Fig. 3).

Name of paper	Publication	Paper summary	Performance evaluation	Advantages	Disadvantages
Multimodal emotion recognition for mental health monitoring: a comprehensive review	Frontiers in Digital Health, 2024. https://doi.org/10.3389/fdgh.2024	This paper reviews state-of-the-art multimodal emotion recognition systems, including facial expression analysis, speech prosody, physiological signals (EEG, HRV), and text sentiment for mental health applications. It discusses emotion AI's role in early screening of depression, anxiety, and stress, real-time monitoring through wearables, and AI-enabled interventions	The performance assessment in the paper is tested on various important points. AI techniques are assessed for their effectiveness in curbing manual labour for planetary data processing, precision in matching or surpassing conventional analysis techniques, and ability to analyze data in real-time during missions. Techniques are also judged for scalability in analyzing large amounts of data and the significance of open-source training data to ensure ongoing improvement Additionally, the evaluation emphasizes the need for interaction	Accuracy is improved, with AI often matching or surpassing traditional methods. AI also enables real-time analysis for timely decisions during missions and is highly scalable to handle large datasets. The use of open-source data fosters continuous improvement, and collaborations between academia and industry drive innovation	The complexity of AI models can make them hard to interpret, and significant computational resources are needed. Integration into existing workflows can be difficult, requiring specialized skills Additionally, ethical and privacy concerns arise with data usage and potential biases in AI Algorithms

Name of paper	Publication	Paper summary	Performance evaluation	Advantages	Disadvantages
			between academia and industry to develop AI-influenced		
Emotion-aware conversational agents for depression and anxiety support	Journal of Medical Internet Research (JMIR), 2025. 10.2196	This paper explores the design and evaluation of chatbots and virtual therapists that integrate emotion AI for empathetic, context-aware responses. The study analyzes Natural Language Processing (NLP)-based emotion recognition from user input and adaptive dialogue strategies to support individuals experiencing depression and anxiety	AI techniques are evaluated for efficiency in autonomous navigation, accuracy in health monitoring, and operational management. Highlighted strengths include handling large datasets, real-time decision-making, and improved communication security with Blockchain	Enhances efficiency, accuracy, and real-time decision-making; automates complex tasks; improves operational management; supports large-scale data analysis; strengthens communication and data security with IoT and Blockchain integration	Relies on high-quality data; AI models are complex and computationally demanding; integration into workflows is challenging; requires specialized skills; legal and ethical issues around data use and algorithmic bias
AI-driven stress detection using wearable biosensors and multimodal data fusion	IEEE Transactions on Affective Computing, 2023. https://doi.org/10.1109/TAFFC.2023	This paper explores the application of advanced machine learning techniques for exoplanet detection and habitability	The paper assesses ML effectiveness in exoplanet detection using models like neural networks and ensemble methods. It highlights	Combining real and synthetic data with CNNs improves detection accuracy, reduces false positives, and enhances	Requires high computational resources; risk of overfitting with synthetic data; creation/validation of synthetic data is time-consuming; effectiveness

Name of paper	Publication	Paper summary	Performance evaluation	Advantages	Disadvantages
		<p>analysis. It discusses exoplanet detection, habitable zone analysis, AI-driven data processing, robotic exploration, and mission planning. The integration of ML algorithms enhances accuracy, efficiency, and precision in identifying potentially habitable planets</p>	<p>improved accuracy, reduced false positives, and superior handling of astronomical datasets compared to traditional methods. ML approaches enhance exoplanet characterization and reliability of detection</p>	<p>robustness. Scalable for large datasets, adaptable to multiple detection scenarios, and supports optimized mission planning with precise observational instruments</p>	<p>depends on data quality; deep learning models are complex and need specialized expertise; ongoing maintenance and risk of algorithmic bias affect reliability</p>

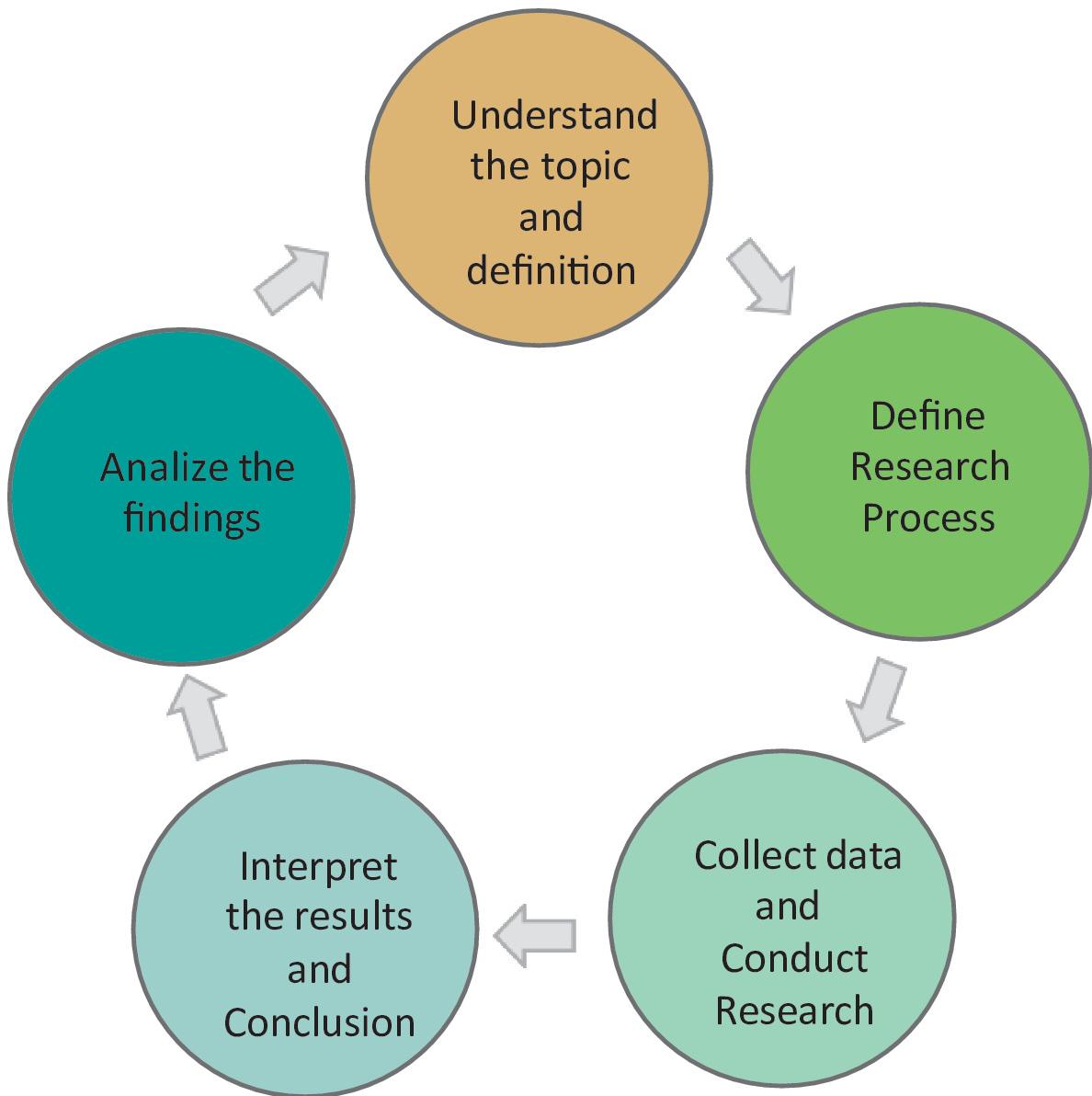


Fig. 3 The progress cycle of a general research methodology

5 Data Quality, Annotation, and Benchmarking in Emotion AI

The reliability and effectiveness of emotion recognition systems fundamentally depend on the quality of the datasets used for training and evaluation. Data quality directly influences the performance, generalizability, and fairness of machine learning models. In Emotion AI, where the subjectivity of human emotional states poses additional

challenges, ensuring precision in data collection and labeling becomes even more critical [34].

5.1 Clinician-Annotated vs. Crowdsourced Labels

Clinician-annotated datasets remain the gold standard, particularly for applications involving mental health, affective disorders, and psychological intervention. Clinical professionals are skilled at identifying subtle emotional signals and understanding comorbidities, making their annotations especially trustworthy. Research consistently shows that clinician-labeled emotion corpora enable the development of models with markedly higher diagnostic value, especially in multimodal frameworks where speech prosody, facial microexpressions, and physiological indicators are integrated [27]. An illustrative example is the IEMOCAP corpus, a widely used multimodal emotion recognition dataset containing audio, visual, and textual data.

Strengths:

Rich multimodal recordings, detailed emotion categories, and high-quality expert annotations make it ideal for training complex models.

Weaknesses:

The dataset is relatively small compared to crowdsourced alternatives and may not fully capture cross-cultural variability.

On the other hand, crowdsourced data offer scalability and demographic diversity, which are advantageous for building models that generalize well across populations. Platforms like Amazon Mechanical Turk and Prolific have been extensively used to collect emotional labels for speech, text, and image stimuli. However, variability in annotator expertise and subjective interpretations of emotion can lead to inconsistencies and increased noise. To address these issues, hybrid approaches are often adopted, wherein clinicians perform initial annotations and crowdworkers validate or expand the dataset under strict quality control protocols [24]. This approach preserves the accuracy of clinical labeling while ensuring the dataset remains sufficiently large to meet the demands of deep learning applications.

5.2 Inter-Rater Reliability and Quality Control

Consistency between annotators is a critical measure of dataset reliability. Inter-rater reliability metrics such as Cohen’s Kappa, Fleiss’ Kappa, and Krippendorff’s Alpha are often utilized to determine inter-rater agreement [35]. High Kappa value signifies that the agreement is over chance levels, which particularly matters for emotion categories that are susceptible to subjective interpretation, e.g., “disgust” or “confusion.” State-of-the-art pipelines include iterative back loops where the annotators are regularly updated to keep their labeling rules in sync during the annotation process [25]. Computer programs are also increasingly used to detect anomaly labels that can distort the distribution of the dataset. In high-risk applications, like health-related emotion recognition, redundant ratings from multiple evaluators are combined using consensus-based or probabilistic model techniques to enhance reliability [28].

5.3 Benchmarking Practices

Benchmarking enables standardized comparison of models, ensuring reproducibility and scientific progress. Historically, datasets such as IEMOCAP, DEAP, and EmoDB have been widely used; however, they often suffer from limited linguistic and cultural diversity, potentially biasing model performance toward certain populations [26].

Emerging datasets, such as the E-THER corpus, are addressing this gap by introducing psycholinguistically grounded annotation protocols, balanced demographic representation, and higher inter-rater agreement thresholds [24]. Benchmarking is evolving beyond static accuracy metrics to include measures of fairness, robustness under noise, and cross-domain generalization, which are now seen as critical for real-world deployment [35].

6 Robustness, Domain Adaptation, and Real-World

Emotion AI models are notoriously sensitive to domain shifts, environmental noise, and cultural variations. Therefore, robustness and adaptability are essential to achieving reliable real-world performance.

6.1 Cross-Cultural Generalization

Emotional expression is highly determined by social and cultural norms. For instance, studies indicate that people with collectivist cultures tend to suppress negative emotional expression in public while those with individualist cultures tend to express such emotions freely [23]. Models learned only from Western data sets tend to misclassify emotions in non-Western populations as much as 35% of the time in some instances [34]. Domain adaptation methods, such as adversarial learning and transfer learning, are now commonly used to close these gaps. For example, English-language corpora-trained models can be transferred to do well on Hindi, Mandarin, or Arabic data using unsupervised domain adaptation, which aligns feature distributions between domains without the need for costly labeled data.

6.2 Noise Handling and Signal Variability

Real-world deployment of Emotion AI has to work in acoustically and visually noisy conditions. For speech-based emotion recognition, there is potential for background noise to mask prosodic features like pitch and intensity, reducing model quality. Data augmentation using synthetic noise, spectral masking, and resilient feature extraction practices like Mel-frequency cepstral coefficients (MFCCs) have been used to improve significantly in noisy situations. Variation in illumination, occlusion, and camera resolution is a challenge to facial expression recognition in computer vision.

6.3 Adversarial Robustness

Adversarial attacks pose unique risks to Emotion AI systems, particularly in security-sensitive applications such as driver monitoring or surveillance. Perturbations imperceptible to the human eye can cause models to misclassify emotions entirely, potentially leading to dangerous outcomes. Countermeasures include adversarial training, where the model is explicitly trained on adversarial examples, and ensemble modeling, which reduces vulnerability by combining multiple classifiers.

7 Multilingual and Cross-Cultural Considerations

Emotion is a universal phenomenon but is expressed differently across cultures, languages, and contexts. Building Emotion AI systems that are equitable and globally relevant requires going beyond English-centric datasets and embracing cultural heterogeneity. Building Emotion AI that is equitable, inclusive, and effective on a global scale, thus requires breaking away from English-biased corpora and including culturally rich emotional patterns.

A direct example of this is available in research that employs the IEMOCAP corpus combined with emotion datasets gathered in East Asian and Middle Eastern countries. Models that are specifically trained on English-language corpora have performed well in classifying emotions in Western populations but do not perform nearly as well when tested with speakers from other cultures. E.g., the facial expressions associated with “surprise” in one culture can be interpreted as “confusion” in another, and vocal prosody associated with “anger” in English may not convey the same emotional significance in other languages. In one case study, combining Western and East Asian data enhanced the accuracy of recognition across cultures by more than 15%, underscoring the value of representative datasets from different cultures. This evidence underlines that emotion is not only biologically based but also socially and culturally constructed. Therefore, cross-cultural calibration becomes necessary to develop emotion recognition systems that function robustly across global communities.

7.1 Need for Diverse Datasets

Current research has shown that over 70% of emotion recognition models are trained primarily on English-language datasets, often collected from Western, educated, industrialized, rich, and democratic (WEIRD) populations. This creates a serious bias; as emotional expression varies widely across geographies. For instance, research shows that in collectivist cultures, emotional expressions like anger may be suppressed in public, whereas in individualistic cultures they are more openly displayed.

7.2 Multilingual Modeling Strategies

Transformers like XLM-R and mBERT have been used for multilingual emotion recognition tasks. They are trained to acquire common representations for languages, facilitating transfer learning from low-resource to high-resource languages. More recent methods use adapter-tuning and prompt-based learning, enabling models to preserve language-specific details while sharing parameters for scale.

A recent large-scale experiment showed that fine-tuning multilingual transformer models on code-mixed data enhanced performance on Hindi-English emotion classification tasks by 18%, which shows the promise of these approaches for real-world use.

7.3 Cross-Cultural Evaluation

Assessment of emotion AI cannot depend entirely on technical measures such as accuracy and F1-score. Culturally respectful assessment protocols are needed. Some studies proposed context-aware measures, e.g., incorporating cultural raters from geographically diverse regions, to avoid overfitting against Western emotional standards.

8 Deployment Architecture and Edge AI

Deploying Emotion AI solutions in clinical and real-world settings introduces engineering and operational challenges that go beyond algorithmic performance.

8.1 Cloud Versus On-Device Processing

Cloud-based solutions offer virtually unlimited computational resources, making them ideal for deep learning models that require high memory and processing power. However, they introduce latency and raise concerns about data privacy, particularly when dealing with sensitive mental health information governed by GDPR or HIPAA.

On-device processing is often referred to as Edge AI and provides low-latency, privacy-preserving solutions by processing data locally on smartphones, wearables, or IoT devices. However, model compression and quantization are required to fit large neural networks on devices with limited computational capabilities.

8.2 Hybrid Edge-Cloud Models

The most promising deployment approach combines edge and cloud infrastructure. In this hybrid architecture, initial inference is performed locally for real-time response, while more complex analytics and periodic model updates occur in the cloud. This architecture ensures privacy, minimizes bandwidth usage, and allows for personalized model refinement over time.

Figure 2 illustrates a typical hybrid deployment model, where feature extraction occurs at the edge, while the cloud provides federated learning updates and aggregates population-level insights. This architecture has been adopted in recent EU-funded digital mental health pilots and has shown improved user engagement and adherence.

8.3 Scalability and Lifecycle Management

Real-world deployments require lifecycle management frameworks that include continuous monitoring, performance drift detection, and automatic retraining pipelines. Federated learning and continual learning have emerged as solutions to ensure that models remain up to date without centralizing sensitive user data.

9 Security Threats and Adversarial Attacks

Emotion AI systems, because they are multimodal and based on sensitive personal information, are confronted with a broad range of security, privacy, and ethical issues. Being robust and trustworthy is paramount, especially when applied to mental health, where mistakes or violations can be dire.

9.1 Deepfake Risks and Manipulation of Emotional Data

Deepfakes and synthetic media represent one of the most critical emerging threats to emotion AI. By fabricating facial expressions, altering speech intonation, or simulating physiological responses, malicious actors can deceive detection systems, leading to inaccurate emotional interpretations and potentially harmful outcomes [28, 34]. For instance, in a widely reported case involving Deeptrace, deepfake technology was used to convincingly mimic a CEO’s voice, enabling a fraudulent transfer of funds —demonstrating how easily synthetic cues can manipulate trust-based systems. In a similar vein, a telepsychiatry platform could mistakenly

classify a synthetic smile as genuine positive affect, skewing therapeutic recommendations.

Current countermeasures rely on multi-layered defense mechanisms. Artifact-based detection identifies inconsistencies at the pixel or frame level, while statistical and temporal pattern analysis detects unnatural movements in facial and physiological signals [28]. More recently, generative models have been repurposed for defense: detectors trained to recognize the subtle artifacts left behind by deepfake algorithms significantly increase detection accuracy.

9.2 Data Poisoning and Model Integrity

Data poisoning attacks constitute the intentional introduction of false or corrupted data into training pipelines with the aim of lowering model performance or injecting concealed biases.

In mental health AI, manipulation would, for instance, lead depressive markers to be labeled as neutral or positive, leading to perilous delay in care [26]. An example of this threat in the real world was when researchers showed that targeted data poisoning could be executed on an image classifier model, successfully changing predictions without significant degradation to overall accuracy—emphasizing how subtle manipulations can be. Protective approaches focus on ongoing monitoring of training data, adversarial training protocols, and human-in-the-loop validation. Furthermore, certified defenses and resilient optimization methods offer a mathematical safety margin, ensuring that outputs of the model are stable even with adversarial contamination [26].

9.3 Privacy and Ethical Compliance

Emotion AI works with naturally sensitive information, like facial expressions, voice recordings, bodily signals, and text messages. Global privacy legislations like GDPR and HIPAA need to be adhered to [10, 25]. Ethical deployment of AI also includes open consent mechanisms, clear communication about data usage, and safe storage facilities to protect against unauthorized use.

Federated learning and differential privacy measures are emerging as top solutions. Federated learning provides local training on end-user devices without revealing raw data to central servers, and differential privacy adds controlled noise to avoid identification of individuals [11, 29].

With integrated XAI layers, these solutions ensure model decisions remain traceable and interpretable [35].

9.4 Regulatory and Cultural Considerations

Global deployment of emotion AI is subject to care regarding local regulation and norms. For instance, facial recognition represents use of biometric information and could be banned in Europe, whereas data sharing policy exists in the United States and Asia [23, 35]. Culturally sensitive measurement is required: the same physiological signal may contain different emotional content across cultures [5, 40]. Ignorance of these differences may reinforce biases and reduce the efficacy of interventions.

9.5 Human Oversight and Governance

Ensuring ethical deployment involves governance mechanisms that engage clinicians, ethicists, and AI specialists. Automated applications in sensitive fields can be prevented from taking place through oversight interventions such as regular audits, ethical review committees, and fail-safe provisions. Ongoing monitoring ensures conformity of AI systems with human values and regulatory requirements across their lifecycle [24, 35].

10 Emerging Trends and Future Directions

Emotion AI is changing fast day by day with massive developments in multimodal integration and strategies for global level deployment. This section describes the nascent trends defining the newer days.

10.1 Multimodal Emotion AI Integration

Enabling the integration of several data streams—text, speech, facial emotions, and physiological signals—increases the accuracy and reliability of the detection of emotion. Newer architectures utilize transformer-based models for text (BERT, RoBERTa), speech (Wav2Vec2.0), and vision (Vision Transformers) through the use of cross-modal attention mechanisms to better fuse features [27, 34]. The integration thus allows for context-sensitive prediction, detecting fine-grained emotional state nuances.

10.2 Personalization and Context Awareness

Personalization involves learning user-specific emotional baselines and accounting for environmental or situational context. For instance, an AI system may recognize that a user's tone of voice changes during late-night conversations, indicating fatigue rather than negative affect [24]. Context-aware emotion AI can significantly improve therapeutic outcomes by reducing false positives and enhancing user engagement.

10.3 Explainable and Transparent AI

Transparency in decision-making is critical for trust, especially in healthcare applications. Techniques such as Layer-wise Relevance Propagation (LRP) and attention visualization allow clinicians and users to understand which features influenced AI predictions [35]. Explainable AI facilitates accountability, supports ethical compliance, and improves adoption by mental health professionals.

10.4 Edge AI and Scalable Deployment

Real-time, large-scale deployment of emotion AI requires hybrid edge-cloud architectures. Edge devices handle immediate inference, reducing latency and preserving privacy, while cloud servers manage model updates, analytics, and aggregation of anonymized data [9, 34]. Scalable deployment ensures continuous learning, adaptation to new populations, and responsiveness to emerging global mental health needs.

10.5 Global Adaptation and Multilingual Capabilities

To achieve worldwide impact, emotion AI must handle linguistic diversity and cultural variability. Multilingual transformers and code-mixed language models facilitate emotion recognition across languages with limited resources [8, 38]. Cross-cultural benchmarking ensures equitable performance, avoiding biases that could exacerbate disparities in mental health care [19, 21, 24].

10.6 Responsible and Ethical AI for Global Health

Looking forward, responsible AI frameworks will become central to emotion AI. Ethical principles, privacy-by-design, fairness, and inclusivity must guide the model development and deployment [24, 35]. Collaboration between policymakers, researchers, clinicians, and patient communities will be essential to create robust, trustworthy, and globally relevant systems.

11 Challenges in Future Prospects

Despite the remarkable progress in Emotion AI for mental health, several challenges remain that may impede its large-scale deployment and effectiveness.

11.1 Data Heterogeneity and Bias

Datasets in emotion AI often suffer from heterogeneity and limited representativeness. Variations in cultural norms, age groups, and socio-economic backgrounds can introduce biases in model predictions, reducing generalizability [24, 26]. Models trained predominantly on Western populations, for instance, may underperform in Asian or African contexts. Addressing such biases requires careful dataset curation, cross-cultural benchmarking, and domain adaptation strategies.

11.2 Real-World Deployment Challenges

Deploying multimodal emotion AI in clinical or telehealth environments involves technical, operational, and social challenges. Real-time inference, sensor calibration, and variable environmental conditions can affect signal quality and model performance [35]. Furthermore, user engagement over long periods remains difficult; individuals may experience fatigue, privacy concerns, or distrust toward AI interventions.

11.3 Integration with Existing Healthcare Systems

Integrating AI-driven emotional assessments into existing healthcare workflows is non-trivial. Clinicians require actionable insights rather than raw outputs, necessitating intuitive interfaces, explainable outputs, and seamless interoperability with electronic health records [23]. Resistance to change and lack of AI literacy among healthcare providers can further slow adoption.

12 Ethical Considerations and Challenges

Ethics remains central to the deployment of Emotion AI, especially in sensitive domains like mental health. Missteps can have profound implications for privacy, trust, and societal impact.

12.1 Privacy and Data Protection

Emotion AI systems collect sensitive biometric, behavioral, and textual data. Failure to secure this information can lead to breaches, misuse, or unauthorized profiling [10, 11]. Techniques such as federated learning, differential privacy, and end-to-end encryption are essential to safeguard user information while preserving model efficacy [25, 29].

12.2 Fairness and Equity

AI models can inadvertently reinforce societal biases. Gender, racial, and cultural biases in datasets may result in inequitable predictions, affecting care outcomes [24, 34]. Continuous auditing, fairness-aware training, and cross-cultural evaluation are necessary to ensure equity in global deployments.

12.3 Transparency and Explainability

Trust in AI is closely tied to explainability. Clinicians and patients must understand how decisions are made, particularly when these influence therapeutic interventions. Explainable AI techniques—such as attention visualization, feature attribution, and causal inferences are critical for transparency and accountability [35].

12.4 Regulatory and Societal Considerations

Global adoption requires adherence to diverse regulatory frameworks. For instance, GDPR in Europe, HIPAA in the United States, and emerging AI regulations in Asia impose constraints on data collection, storage, and algorithmic decision-making [23, 35]. Beyond regulations, societal acceptance hinges on ethical deployment, cultural sensitivity, and active involvement of stakeholders in co-designing AI systems.

13 Observations

From the synthesis of current literature and practice, several observations emerge:

- Multimodal integration enhances accuracy: Combining text, speech, facial, and physiological modalities provides richer emotional context, improving the reliability of AI predictions [27, 34]

- Personalization is essential: Accounting for individual emotional baselines and cultural norms significantly improves engagement and efficacy in therapeutic contexts [24].
- Robustness and resilience remain challenges: Systems must handle noise, adversarial attacks, and environmental variability to maintain clinical utility [26].
- Ethics and governance are non-negotiable: Privacy, explainability, and fairness are critical for trust and sustainable deployment [10, 24].

These observations suggest that while Emotion AI has transformative potential for global mental health, careful design, validation, and governance are prerequisites for real-world impact.

14 Conclusion

Emotion AI is reshaping how mental health is understood, monitored, and supported, moving far beyond traditional evaluation techniques toward intelligent, adaptive systems. By leveraging multimodal data—capturing vocal tone, facial dynamics, textual expression, and physiological signals—advanced algorithms can reveal nuanced emotional states that standard assessments may overlook. This enables timely, scalable mental health support that can be personalized to each individual’s context and needs. However, realizing the full potential of these technologies requires confronting persistent challenges. Ensuring the quality and inclusiveness of datasets is essential to prevent misclassification and inequitable outcomes. Ethical and privacy concerns must be addressed with robust safeguards that protect sensitive personal information. Just as importantly, integrating AI into real-world clinical workflows demands careful alignment with existing medical practices and regulatory standards. Only through rigorous validation, ethical governance, and thoughtful design can Emotion AI emerge as a trusted and effective component of mental health care.

14.1 Future Directions

Global-scale, culturally diverse datasets: Efforts should focus on creating datasets that encompass linguistic, cultural, and socio-economic diversity, enabling fair and accurate models globally [24, 26]. Efforts should focus on creating global-scale, culturally diverse datasets that encompass linguistic,

cultural, and socio-economic diversity, enabling fair and accurate models worldwide [24, 26].

Among the various directions, building culturally and linguistically diverse datasets stands out as the most urgent recommendation for researchers. Without inclusive and representative data, even the most advanced models risk reinforcing existing inequities and failing to generalize effectively across populations [24, 26]. Expanding dataset diversity will provide the foundation needed for fair, accurate, and globally relevant emotion recognition systems.

- Federated and privacy-preserving AI: Techniques such as federated learning, differential privacy, and on-device processing can enhance model performance while safeguarding sensitive personal information [25, 29].
- Explainable and human-centric AI: Transparent and interpretable systems will support clinician trust and ensure responsible use in mental health settings [35].
- Longitudinal clinical validation: Real-world studies are needed to assess efficacy, adherence, and long-term psychological outcomes across diverse populations [14, 39].
- Ethical frameworks and regulation: Establishing clear, collaborative ethical guidelines aligned with local and global standards will be critical for responsible and sustainable deployment [23, 35].

By prioritizing dataset diversity, researchers can create a strong, equitable foundation upon which privacy-preserving methods, explainability, clinical validation, and ethical governance can be effectively built.

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A Conceptual Framework for Adaptive Student Assessment Using AI-Driven Recommendations and Facial Expression Recognition

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Abstract

Nowadays, Student Facial Expression Recognition Systems (SFER) are increasingly used in the context of smart classrooms, as they help educators assess their students' emotional and engagement states during courses. However, the full potential of utilising the output of these systems has not yet been fully explored. In this chapter, we present a conceptual framework that explores how the output of an SFER system can be used to build a recommendation generator, a tool that helps instructors assess and respond

to student engagement both during and after class sessions. We propose a system that integrates a Generative AI-based Recommendation engine designed to guide teachers in adjusting their teaching methods and improving overall classroom strategies. As part of this framework, we present the Smart Classroom Monitoring System (SCMS), a complete pipeline from data acquisition to dashboard visualisation alongside the AI Recommendation Generator Engine (AI-RGE). The AI-RGE, built using GPT-4o customisation using the OpenAI platform, generates recommendations for instructional actions based on students' detected engagement states. We believe that this framework offers a promising advance for the education sector, providing valuable support for instructors seeking to optimise student engagement and learning outcomes. Future research is recommended to implement the proposed system in diverse classroom settings and further investigate its long-term impact on teaching effectiveness.

Keywords Adaptive teaching – AI recommender – Generative AI in education – Feedback generator – GPT-4 – Smart classroom monitoring – Student engagement

1 Introduction

Student monitoring systems provide many benefits, including enhancing classroom management, improving student engagement, and optimising teaching performance.

In the literature, various systems have been proposed for tracking and monitoring students in classroom environments. These systems are typically classified as either student-centred [1, 2] or teacher-centred. Since student performance is often viewed as a reflection of effective teaching, many authors emphasise student-centred or hybrid systems, which offer instructors the opportunity to monitor not only their students' learning progress but also their own teaching effectiveness.

One promising direction in classroom monitoring is the use of vision-based systems such as Facial Expression Recognition (FER) [3], which provide instructors with real-time insights into students' affective states during class sessions. This information can help measure students' degree of involvement and concentration. However, none of the existing studies

have fully explored how to utilise the outputs of these systems for continuous student monitoring and adaptive instructional feedback. Most recent works have concentrated on improving SFER algorithm performance and model accuracy, with only modest suggestions for actionable outcomes [4, 5].

In this work, we address this gap by integrating a generative AI-based recommendation system that processes the outputs of the SFER system and translates them into practical recommendations to help instructors adapt their teaching strategies in real time.

This chapter presents the complete pipeline of the SFER system, starting from students video acquisition during classroom sessions, to the visual presentation of the analysed data through well-structured dashboards. These dashboards are designed to be easy-to-use for both instructors and faculty administrators, thereby facilitating actionable insights. This contribution will provide researchers and educational stakeholders with a practical framework for developing, improving, or creating student monitoring systems based on FER technology.

We organise this article as follows: Sect. 2 presents the proposed methodology, Sect. 3 discusses the results, and Sect. 4 concludes with insights and suggestions for future research directions.

2 Related Works

Evaluating students based only on their outcomes, such as grades or exam results, might not provide clear insight [6]. Instead, it is important to focus on the learning process itself. By observing how the students engage with their teaching strategies in real-time, educators can recognise difficulties early and adjust their approach to better support each student's unique learning needs.

Several studies have adopted FER systems to assess classroom engagement. For example, Ashwin et al. [7] proposed a methodology based on a convolutional neural network (CNN) architecture to detect students' affective states during lectures, aiming to estimate an overall classroom engagement score. The results were shared with faculty members for further analysis and to guide improvements in teaching strategies. Gupta et al. [8] suggested basic feedback to faculty members, such as deducing that if a

“High Positive Affect” is observed consistently over 70% of a video segment, it may indicate:

- An effective teaching style and strategy;
- High levels of student interest and engagement.

Another notable study by Summer et al. [9] used AffectNet as the foundational architecture, training their model on a large spontaneous dataset to categorise student engagement. These findings highlight the effectiveness of deep learning approaches, particularly CNN architectures such as GoogleNet and ResNet-50, across diverse settings and datasets, significantly improving the accuracy of FER systems.

In addition to recent studies that explored novel architectures, such as Vision Transformers, to enhance the accuracy of SFER models [10, 11], a relevant study published in 2025 [12] advanced this line of research by not only measuring students’ emotional engagement but also analyzing its correlation with academic outcomes through a facial expression recognition system (MP-FERS). The findings demonstrated the effectiveness of such systems and their ability to improve the consistency of student performance across different ability levels.

While such insights are valuable, they represent the farthest current research has gone in leveraging SFER system outputs. To our knowledge, no study has proposed or implemented a complete pipeline from acquisition to final utilisation by the end user (i.e., the instructor) that transforms SFER data into meaningful, actionable recommendations.

3 Proposed Framework

The Smart Classroom Monitoring System is an AI-driven framework designed to visually track students’ affective states during classroom sessions, extract engagement information, and transform it into actionable recommendations to help instructors adapt their teaching strategies.

As shown in Fig. 1, our proposed system pipeline is divided into four main blocks:

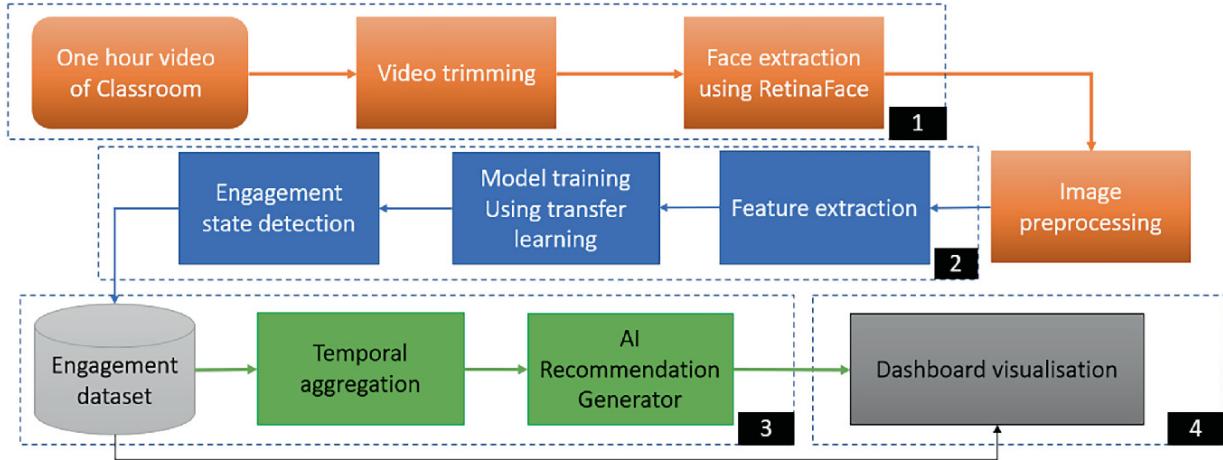


Fig. 1 The framework of the student engagement assessment tool based on FER and AI-based recommendations

1. Block 1: Data Acquisition and Face Extraction This initial step involves capturing video footage of the classroom using a high-resolution frontal camera to ensure a clear, unobstructed view of the students. The recorded video is processed in real-time and segmented into 5 s clips. This interval is chosen to optimise memory usage and avoid overloading computational resources.

Each video segment is time stamped to maintain synchronisation with the original session timeline. Next, student faces are extracted from individual video frames using RetinaFace [13], a state-of-the-art deep learning model known for its high accuracy in real-time face detection, even under occlusions such as scarves, glasses, or hats.

The extracted face images are then preprocessed (resized, normalised, etc.) and prepared for the next stage.

2. Block 2: Engagement State Detection

In this phase, facial features are extracted from each preprocessed face image and encoded into compact feature vectors representing the unique characteristics of the expression. These vectors are fed into a pre-trained deep learning model that classifies the engagement level in each frame, typically as either Engaged or Not Engaged.

3. Block 3: AI-Based Recommendation Generator

The predicted engagement states from Block 2 are compiled and passed to an AI recommendation engine. This component is powered by

Chatgpt-4, which processes the engagement data as input prompts and generates personalised teaching recommendations. The suggestions aim to help instructors adjust their methods in real-time or for future sessions.

4. **Block 4: Dashboard Visualization** Finally, all generated data including engagement levels and AI-driven recommendations are compiled into an interactive dashboard. This interface offers intuitive visualisations of student engagement over time and integrates real-time feedback to assist instructors. The dashboard provides actionable insights, making it easier for instructors to assess the effectiveness of their teaching methods and identify areas for improvement.

A detailed explanation and visual demonstration of this interface will be presented in the following sections.

3.1 Student Engagement Model Implementation

To build a robust and reliable SFER system, we used a customised and adapted dataset, specifically designed for student engagement classification, “StuEmo24” [14]. We fine-tuned a pre-trained MobileNet model [15] on this dataset, and as a result, we accurately classified students’ engagement levels based on their facial expressions. Figure 2 presents the framework of the SFER system.

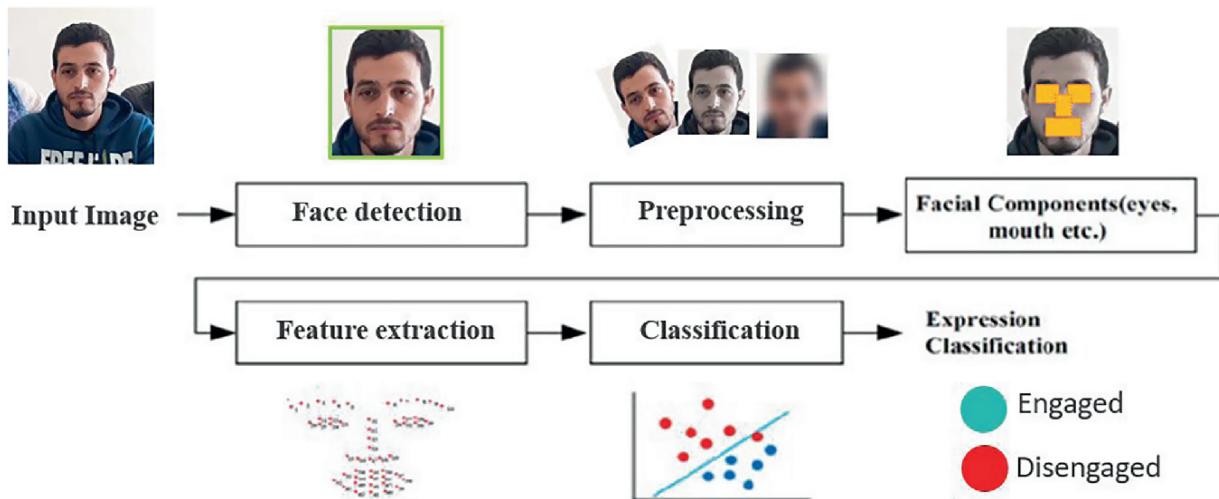


Fig. 2 The framework of the SFER system

Dataset description StuEmo24 is a spontaneous facial expression dataset developed specifically to detect student engagement in classroom settings. It contains 718 annotated frames collected from 11 participants, captured using a high-resolution 50 MP camera from a frontal view to ensure clear facial visibility. Participants were informed that the experiment involved recording their videos during lectures and using their images for research purposes. They were also made aware that their images might be included in a publicly available research article and dataset. However, to ensure natural classroom behavior, participants were not explicitly told the exact start time of the recordings or which specific portions of the videos would be analysed. This approach aimed to capture authentic engagement states without influencing their reactions.

The dataset was annotated using a combination of manual labelling and expert review for higher reliability and accuracy. StuEmo24 includes two engagement classes: Engaged and Disengaged, and has been validated using state-of-the-art deep learning models. The dataset is divided into 80% training, 10% validation, and 10% testing sets. It is specifically designed for classroom-based applications, making it a valuable resource for developing and evaluating facial expression recognition systems for monitoring student engagement. The dataset is available upon request via email.

Engagement detection model To train the engagement detection model, we use a pretrained MobileNet architecture as the base model and fine-tune its parameters for our specific task. MobileNet is a lightweight deep neural network that employs depthwise separable convolutions, which significantly reduce the number of parameters and computational cost. Its efficiency makes it particularly well-suited for real-time applications and deployment on resource-constrained devices, such as mobile platforms. For training, the model is configured to accept 48×48 grayscale input images. We freeze all layers except the fully connected layers, allowing only the latter to be trained. An average pooling operation is applied at the 14th layer to reduce spatial dimensions and enhance feature representation. The model is trained with a batch size of 25, using Softmax as the activation function for classification, and the Adam optimiser for efficient convergence. Since our task involves binary classification (Engaged vs. Disengaged), we use Binary Cross-Entropy as the loss function. Table 1 summarises the model configuration and key parameters used during training.

Table 1 Model features details

Feature	Batch size	Epochs	Activation function	Optimizer	LR	Loss function
Details	25	50	Softmax	Adam	0.01	Binary cross entropy

Data acquisition and pre-processing The data acquisition process begins with capturing videos of students during the course session using a frontal high-resolution camera to ensure clear visibility of facial features. The recorded videos are trimmed into short segments, and individual frames are extracted from each segment.

After extracting and cropping the face images from these frames, we apply a series of image preprocessing steps using the OpenCV library. First, each image is converted to grayscale to reduce complexity while keeping important facial features. Then, the images are resized to match the input dimensions required by the model. Following that, we perform normalisation to scale the pixel values between 0 and 1, in order to ensure consistent input for the neural network.

Finally, the preprocessed images are fed into the engagement detection model to predict the engagement state of each student, and this preprocessing pipeline is executed in real-time during data acquisition, enabling immediate engagement detection.

3.2 Generative AI Recommender Module

The output data coming from the SFER system is formatted to serve as input for our proposed AI-based Recommendation Generator Engine (AI-RGE), which is built using the OpenAI framework. In this section, we provide a comprehensive details on the implementation, including the system architecture, code structure, and the prompt engineering process used for generating pedagogical recommendations.

Developing the AI-RGE generator The OpenAI platform provides the capability to configure and adapt GPT models as customised ChatGPTs for specific use cases [16]. This customisation allows the system to deliver context-aware and task-specific recommendations, overcoming the limitations of general-purpose GPT models that may lack field-specific focus and produce irrelevant or biased responses.

The development of the AI-RGE module follows three main steps:

1. Preparation of engagement data generated by the SFER module.
2. Configuration of the GPT-4o model, adapted to interpret the engagement states.
3. Prompt engineering, where we design and refine input prompts to guide the model's responses effectively.

The module then generates recommendations based on the processed engagement data. This pipeline ensures that end users, such as instructors or faculty members, receive meaningful, personalised insights from student engagement patterns. The generated suggestions not only help improve teaching strategies but also adapt to students' difficulties. Figure 3 presents the AI-RGE creation process.

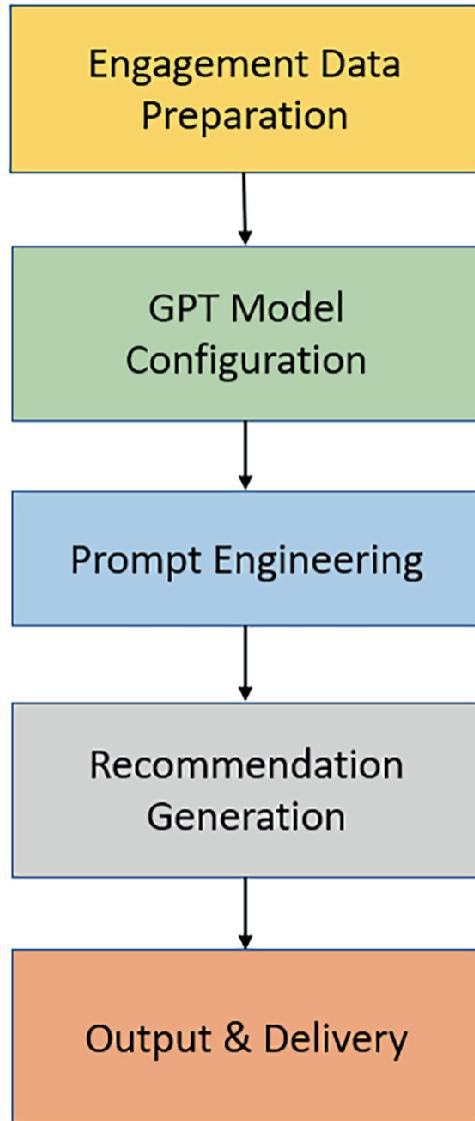


Fig. 3 The process of the AI-RGE module

Preparation of engagement data The input to our AI Recommendation Generator Engine (AI-RGE) is derived from the output of the SFER system, provided in the form of a structured table (to be presented in the Results and Discussion section). This table contains engagement data collected from a real classroom setting. To evaluate the functionality of our recommendation engine, we simulate the input by generating synthetic engagement data for a set of fictional students. Specifically, we calculate the average engagement level of each student over a 40 min session of a computer vision course, along with the overall classroom engagement average. This approach ensures that the system can be tested under a variety of conditions without

requiring repeated classroom experiments. Thus, the use of synthetic data does not alter the validity of the engagement recognition results; it only complements the evaluation of the recommender system.

Below is the Python code snippet used to simulate the input data:

```
1 # ===== Moroccan student names =====
2 moroccan_names = [
3     "Youssef", "Fatima", "Omar", "Khadija", "Amine",
4     "Salma", "Hicham", "Amina", "Karim", "Zahra",
5     "Anas", "Nadia", "Mohammed", "Imane", "Rachid",
6     "Laila", "Said", "Hanane", "Ahmed", "Soukaina"
7 ]
8
9 num_students = len(moroccan_names)
10 num_time_segments = 40 # e.g., 40 time segments (1 per
11             minute of a 40-min class)
12
13 # ===== Generate random engagement data =====
14 data = []
15
16 for student in moroccan_names:
17     engagement_scores = [round(random.uniform(0.3, 1.0), 2)
18                           for _ in range(num_time_segments)]
19     avg_engagement = round(sum(engagement_scores) /
20                             num_time_segments * 100, 2)
21     data.append({
22         'student': student,
23         'engagement_scores': engagement_scores,
24         'average_engagement': avg_engagement
25     })
26
27 df = pd.DataFrame(data)
28 class_average = round(df['average_engagement'].mean(), 2)
29
30 print(df[['student', 'average_engagement']])
31 print(f"\nClass Average Engagement: {class_average}%")
```

Listening 1 Generating synthetic engagement data for Moroccan students

GPT-4o model configuration We configure the GPT-4o model on the OpenAI platform, which facilitates using GPT as a base model. To get started, we only need to purchase credits and generate an API key.

```

1 import openai
2
3 client = openai.OpenAI(
4     api_key="# ##### T3B1bkFJKvFnYHae-01E6aGYZCk9HHYAHdz-2
5         AKpsJoQ ##### HZAAOC1JqyBwOdH28rT-Ym0vkV0mgA #####"
6         # To Replace with the personalised OpenAI API Key
7 )

```

Listening 2 Configuring GPT base code

Prompt engineering After preparing the engagement data and configuring the GPT-4o model, we proceed to prompt engineering. The code implementation is as follows:

```

1
2 gpt_prompt = f"""
3 You are an educational engagement advisor. Given the
4     following student engagement data and class context,
5     analyze it and provide clear, actionable feedback for the
6     teacher.
7
8 DATA
9 {engagement_summary}
10
11 CONTEXT
12 This data was collected during a 40-minute science class
13     focused on "Computer vision".
14
15 YOUR TASK
16 - List 2 to 3 key engagement observations.
17 - Suggest strategies for improving engagement for students
18     with < 50%.
19 - Recommend 2 whole-class engagement strategies.
20 """

```

Listening 3 Preparing GPT prompt

Generating Recommendations We send the configured GPT prompt to the model and generate recommendations using the following code:

```

1 response = client.chat.completions.create(
2     model="gpt-4",
3     messages=[
4         {"role": "system", "content": "You are a helpful
5             educational engagement advisor."},
6         {"role": "user", "content": gpt_prompt}
7     ],
8     temperature=0.7,
9     max_tokens=800
10)
11 # ===== Output GPT Recommendations =====
12 print("\n--- GPT Recommendations ---")
13 print(response.choices[0].message.content.strip())

```

Listening 4 Sending prompt to GPT

4 Results and Discussion

SFER model evaluation We trained several state-of-the-art deep learning models on the StuEmo24 dataset, including EfficientNet, ResNet, InceptionV3, VGG16, DenseNet, and MobileNet. Among these, MobileNet achieved the highest accuracy, reaching 98%, making it the most effective model for our task. Figure 4 illustrates a comparative graph showing the accuracy performance of each model.

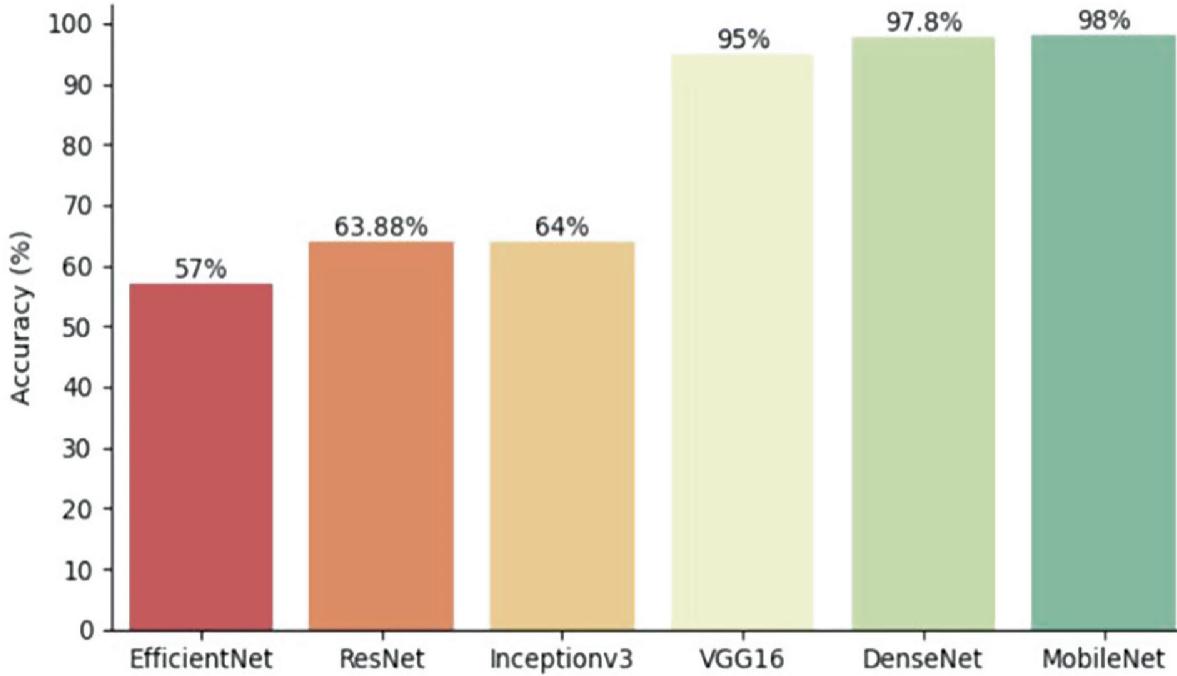


Fig. 4 Accuracy of state-of-the art deep learning models trained on StuEmo24

Despite these promising results, it is crucial to identify some limitations in our approach. Although we took into consideration common occlusions such as scarves, beards, and glasses, we did not address variations in lighting conditions. As a result, the model's performance may decline when applied in environments with different illumination.

Nonetheless, a key advantage of using the StuEmo24 dataset is that it was collected in the wild, under real classroom conditions, which enhances the robustness and relevance of the training data for real-world deployment.

The model is now capable of detecting the engagement state of students in real time during course sessions. The resulting engagement data is automatically stored in a database, with each entry containing key features as summarized in Fig. 5.

Timestamp	Student ID	Face Position (x, y, w, h)	Engagement Label	Engagement state (%)	Confidence Score
04/03/2025 10:44:50	S001	100, 150, 200, 250	Engaged	66%	0.92
04/03/2025 10:44:55	S001	105, 155, 200, 250	Engaged	66%	0.89
04/03/2025 10:45:00	S001	110, 160, 200, 250	Engaged	66%	0.75
04/03/2025 10:45:05	S001	115, 165, 200, 250	Engaged	66%	0.68
04/03/2025 10:45:10	S001	105, 155, 200, 250	Disengaged	66%	0.88
04/03/2025 10:45:15	S001	110, 160, 200, 250	Disengaged	66%	0.92
04/03/2025 10:45:20	S001	115, 165, 200, 250	Disengaged	50%	0.89
04/03/2025 10:45:25	S001	105, 160, 200, 250	Engaged	50%	0.75
04/03/2025 10:45:30	S001	115, 165, 200, 250	Engaged	50%	0.68
04/03/2025 10:45:35	S001	105, 160, 200, 250	Engaged	50%	0.85
04/03/2025 10:45:40	S001	115, 165, 202, 251	Disengaged	50%	0.89
04/03/2025 10:45:45	S001	105, 160, 204, 251	Disengaged	50%	0.75

Fig. 5 Engagement data collected from the SFER system output

AI-RGE module The output of our AI-RGE recommender system responds to the given prompt by generating insights into students' engagement levels. It provides general observations and identifies students with either high or low engagement rates. When a student's engagement is low or falls below the class average, the AI-RGE recommender suggests customised strategies tailored to their needs. For example:

The topic may be complex for Amina and Ahmed, as they have the lowest engagement rates compared to the classroom average. You may consider holding one-on-one conversations with them to better understand their difficulties and interests. Assignments and activities

can be personalised to make the content more relevant to their experiences.

In addition to individual strategies, the recommender can also propose classwide engagement approaches based on overall classroom engagement levels. For instance:

Collaborative Learning: Incorporate group activities and projects that allow students to learn from one another. This encourages active participation and can boost engagement, especially when the current class engagement rate is lower than the desired target.

Example of the generated recommendation is presented in Fig. 6.

```
Class Average Engagement: 65.58%
--- GPT Recommendations ---
OBSERVATIONS:
1. The class average engagement is 65.58%, which is relatively moderate. This means that there's room to improve student engagement in the class overall.
2. The two students with the highest engagement rates are Imane (71.57%) and Amine (70.78%), which shows that the content is accessible and interesting to some students.
3. The students with the lowest engagement rates are Ahmed (60.35%) and Soukaina (61.85%), suggesting that these students may need additional support or different strategies to stay engaged.

STRATEGIES FOR STUDENTS WITH < 50% ENGAGEMENT:
There are no students with less than 50% engagement. However, for the students with the lowest engagement rates, Ahmed and Soukaina, here are some suggestions:
1. Personalized Learning: Have a one-on-one conversation with them to understand their difficulties and interests. Tailor assignments and activities in a way that makes the class content more relevant to their experiences.
2. Incremental Challenges: Break down complex topics into smaller, manageable parts. Gradually increase difficulty as they gain confidence and understanding in the subject.

WHOLE-CLASS ENGAGEMENT STRATEGIES:
1. Collaborative Learning: Incorporate group activities and projects where students can learn from each other. This encourages active participation and enhances student engagement.
2. Interactive Teaching Strategies: Utilize interactive teaching strategies such as quizzes, debates, and hands-on experiments. This can make the class more dynamic and engaging.
3. Real-World Connections: Try to tie the lessons to real-world applications, especially in the field of computer vision. This could involve discussing how this technology is used in various industries, or inviting a guest speaker who works in this field. This can make the subject matter more interesting and relevant to the students.
```

Fig. 6 Example of generated recommendation with AI-RGE

Dashboard visualisation The final component of the Smart Classroom Monitoring System (SCMS) is the visualisation of results through an interactive dashboard, designed for ease of use and clear interpretation. This dashboard integrates real-time and summary data in a simplified, user-friendly format, enabling instructors to effectively assess and respond to their students' difficulties during the session.

The dashboard consists of five key panels as shown in Fig. 7:

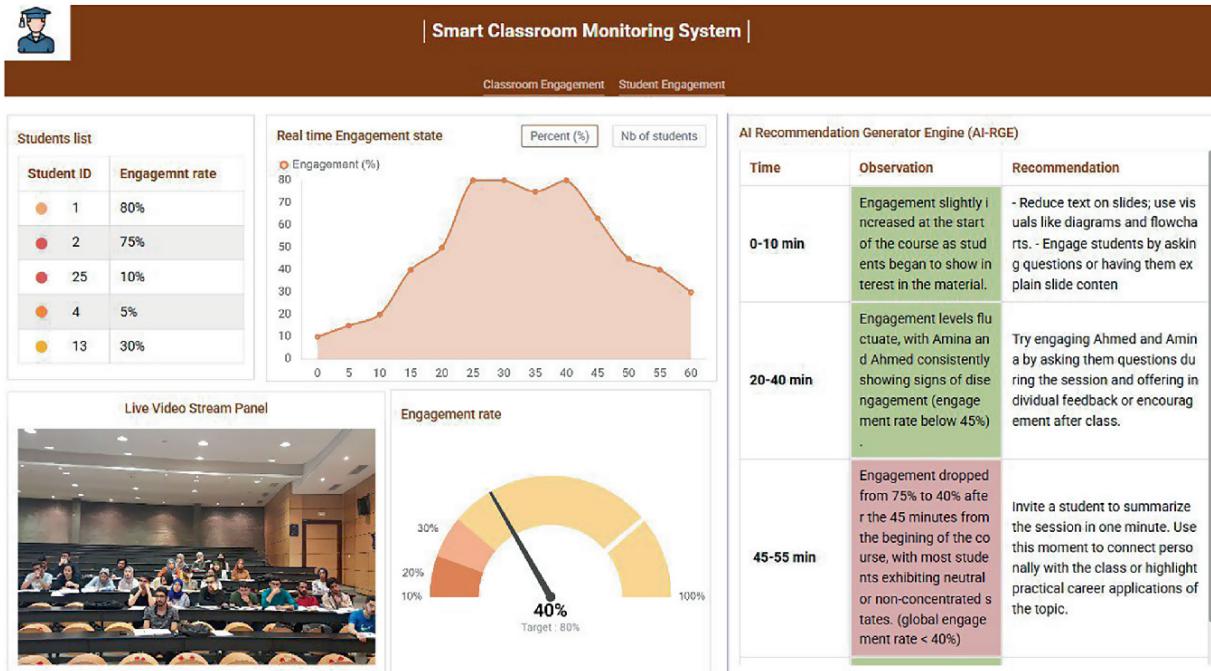


Fig. 7 Illustration of the SCMS system dashboard visualisation

- 1. Student List Panel:** It displays the list of student IDs along with their corresponding engagement rates. This allows the instructor to monitor individual students and track their overall engagement level from the beginning of the session.
- 2. Real-Time Engagement Graph:** It is a dynamic line graph that visualises the fluctuation of engagement levels for each student throughout the session in real time. Also, it provides instant feedback on how students are responding to different parts of the lesson.
- 3. Live Video Stream:** It shows a live stream of the classroom, allowing the instructor to observe student behaviour in real time or review it post-session. This feature enhances transparency and contextual understanding of engagement patterns.
- 4. Engagement Rate Gauge:** It is a circular gauge that indicates the overall engagement level of the classroom at any given moment. This visual tool offers a quick and intuitive assessment of classroom dynamics.

5. **AI Recommendation Generator Engine (AI-RGE):** It presents a table of recommendations generated by the AI engine based on real time engagement data. This panel is activated when significant events occur, such as a consistent drop in engagement for over 10 min, proposing suggestions like taking a short break, changing activities, or offering personalised interventions for specific disengaged students.
-

5 Conclusion and Perspectives

The main goal of our study is to propose a conceptual framework for developing a smart engagement monitoring system that generates adaptive recommendations based on the GPT-4o language model. This system has the potential to improve teaching strategies by guiding instructors in real-time with actionable suggestions aimed at maintaining or improving student engagement during classroom sessions. To the best of our knowledge, this is the first study to deploy and explore a Student Facial Expression Recognition (SFER) system integrated with an AI Recommendation Generator Engine (AI-RGE). The proposed engine utilises the engagement output from the SFER module and transforms it into meaningful, context-aware recommendations that instructors can apply immediately.

We trained our SFER model using the StuEmo24 dataset and fine-tuned a pretrained MobileNet model, which achieved an accuracy of 98%. To generate recommendations, we integrated the latest GPT-4o model, and applied prompt engineering techniques to enhance recommendation quality, minimise bias, and ensure context-adaptive responses customised to real classroom conditions.

Moving forward, we propose the deployment of the complete framework in diverse classroom environments and instructional contexts, with the goal of assessing its efficiency through longitudinal studies. Additionally, the integration of performance metrics such as quizzes and test results will offer deeper insights into both student engagement and the effectiveness of the generated recommendations. Moreover, the system can be integrated with Learning Management Systems (LMS), enabling automated tracking of engagement indicators alongside academic performance, personalised feedback, and simplified reporting for instructors.

Ultimately, our objective is to contribute to the advancement of the teaching and learning experience by leveraging latest AI technologies to support and improve educational practices.

Glossary of Acronyms

Acronym Meaning

FER Facial Emotion Recognition

SFER Student Facial Emotion Recognition

SCMS Smart Classroom Monitoring System

AI-RGE AI Recommendation Generator Engine

LMS Learning Management System

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Integrating AI-Driven Facial Emotion Recognition into E-Learning Systems: Sustainable Educational Markets Through Interdisciplinary Innovations

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Abstract

This interdisciplinary study examines AI-driven Facial Emotion Recognition (FER) integration into e-learning systems to tackle engagement deficits and promote sustainable educational markets. FER enables adaptive learning via real-time emotional feedback, potentially boosting engagement and reducing attrition. However, challenges such as algorithmic biases, privacy concerns, cultural misalignments, and infrastructural barriers hinder adoption. A PRISMA-guided systematic review of 140 high-impact studies reveals gaps in scalability, ethical governance, and cross-cultural validation. We propose a sustainable framework with four pillars: pedagogically grounded adaptive learning, transparent ethical protocols (GDPR/FERPA-compliant), culturally inclusive emotion modeling, and cost-efficient cloud infrastructure. This framework mitigates risks like automation bias and surveillance capitalism through interdisciplinary collaboration in computer science, education, and ethics. Practical recommendations include public-private partnerships and decolonized AI design, while policy advocacy

emphasizes equitable funding and explainable AI standards. Responsibly implemented FER could yield equitable learning outcomes and economic savings, fostering long-term EdTech viability (Dhawan in *J. Educ. Technol. Syst.* 49:5–22, 2020; Zawacki-Richter et al. in Article 39, 2019;).

Keywords Facial emotion recognition (FER) – E-learning engagement – Ethical AI – Algorithmic bias – Interdisciplinary collaboration – Sustainable EdTech – Adaptive learning – Cultural adaptation

1 Introduction

1.1 Background

The global e-learning market has surged due to technological advancements and events like the COVID-19 pandemic, evolving from supplementary tools to core educational platforms [20, 43]. However, sustainability hinges on equitable access and proven outcomes, amid challenges like disengagement and high attrition rates [60, 69]. AI, particularly affective computing, offers promise by detecting emotional states to personalize learning [15, 53].

Emotions play a pivotal role in learning, influencing attention, motivation, and performance [32, 50]. Positive emotions enhance engagement, while negative ones increase dropout risks, especially in online settings [17]. Advances in FER using CNNs enable real-time emotion mapping from facial cues, supported by datasets like AffectNet [38, 46]. Multimodal integration with vocal or physiological data improves accuracy [21, 56].

Sustainability in EdTech extends beyond economics to include social justice, pedagogical efficacy, and scalability [12, 65]. This requires interdisciplinary efforts integrating pedagogy, computing, psychology, ethics, and business [13, 35].

1.2 Problem Statement

E-learning systems suffer from high disengagement and attrition rates (>30% in MOOCs), lacking real-time emotional adaptation, which exacerbates isolation and equity gaps [2].

Research Gaps:

- Scalability strategies are addressed in only 12% of the literature [21].
- Ethical governance and privacy protocols are underdeveloped, risking violations [26, 70].
- Cross-cultural validation is limited, with 40% failure in non-Western contexts.
- Pedagogical misalignment, ignoring contextual emotions [28].
- Infrastructural barriers excluding under-resourced areas [14].

1.3 Research Questions and Objectives

This study aims to develop a sustainable FER framework for e-learning.

Core RQs include:

- RQ1–3: Pedagogical integration (e.g., scaffolding via FER, context factors, learner agency).
- RQ4–6: Technical enhancements (e.g., transfer learning, sensor fusion, adaptation thresholds).
- RQ7–9: Impact quantification (e.g., causal relationships, fairness, self-regulation).
- RQ10–12: Governance models (e.g., consent, interoperability, sustainability indicators).

Chapter roadmap: Literature review (Sect. 2), methodology (Sect. 3), findings (Sect. 4), framework (Sect. 5), implications (Sect. 6), and conclusion (Sect. 7).

2 Literature Review

2.1 AI in E-Learning Systems:

AI, particularly Facial Emotion Recognition (FER), revolutionizes e-learning by enabling personalized, interactive experiences [15, 58]. It allows real-time adjustment of content difficulty and pacing based on inferred cognitive-affective states, significantly reducing frustration and disengagement [4, 37]. Emotion-sensitive systems demonstrably improve knowledge retention by 23–41% compared to static platforms, especially in complex STEM domains [28, 11, 35]. The COVID-19 pandemic accelerated adoption but exposed infrastructure dependencies and limitations in low-bandwidth affect detection [20]. Research has focused on

multimodal sensor fusion to enhance robustness, coupled with ethical frameworks compliant with global data regulations [13, 65].

2.2 Facial Emotion Recognition Tech & Apps:

While Transformers and CNNs achieve >92% FER accuracy in laboratories, real-world classroom performance drops (72–85%) because of lighting variations and cultural expression differences [38]. Advanced approaches integrate Action Unit detection (FACS) and temporal modeling to identify pedagogically relevant states like productive confusion or unproductive frustration [36]. Applications include adaptive testing adjusting for anxiety [50], emotionally responsive virtual tutors, and peer matching based on emotional compatibility. Corporate FER implementations show 34% higher completion and 27% better skill transfer. However, cultural acceptance varies significantly, with East Asian learners expressing ~ 40% higher privacy concerns than Europeans [57].

2.3 Interdisciplinary Innovation:

Effective FER requires integrating computer science, educational psychology, neuroscience, and ethics [27, 41]. Learning theories (e.g., cognitive load theory, constructivism) are essential for translating emotional data into pedagogical actions. Neuroscience has revealed how affective contexts engage memory systems (hippocampal-amygadala loops), guiding optimal FER timing [31, 64]. Ethicists caution against “surveillance capitalism” and advocate learner-centric data stewardship [70]. Success stories include MIT’s Affective Learning Companion (co-designed with tutors), which reduced calculus dropout by 29% via frustration-triggered support [53], and the EU CEEDs project, which boosted history engagement by 31% using emotion-aware VR. Interdisciplinary teams develop systems 4.7 × more pedagogically effective than technocentric approaches [51].

2.4 Sustainable EdTech Markets:

AI FER offers economic viability: a 10% reduction in attrition can save mid-sized universities ~ \$1.6 M annually [1, 17]. However, lifecycle analysis reveals environmental costs (e.g., GPU systems consuming 283 kWh/day per 10 k students), necessitating energy-efficient hardware [12, 63]. Social sustainability is critical, as biased FER systems (15–34% less

accurate for darker-skinned women) risk widening achievement gaps [7, 47]. Ethical adoption demands alignment with UNESCO guidelines, including auditable bias mitigation and avoiding manipulation [26, 65]. Companies prioritizing pedagogical ROI (learning gains versus cost) extend adoption cycles by 78% [24, 33]. Scalability faces interoperability hurdles, only 12% of major LMSs natively support FER APIs, although emerging IEEE standards offer hope [21, 67] (Table 1).

Table 1 Pillars of sustainable FER integration

Pillar	Description	Key challenges	Major studies
Ethical sustainability	Transparent protocols, bias mitigation	Privacy violations, algorithmic bias	[11, 26]
Pedagogical sustainability	Adaptive learning aligned with theories	Misalignment with emotions	[28, 31]
Economic sustainability	ROI through retention	High costs, interoperability	[1, 21]
Cultural sustainability	Inclusive modeling	Western bias, failure in diverse contexts	

Source Authors' collation from various sources specified above

3 Research Methodology

3.1 Systematic Literature Review (SLR)

3.1.1 Protocol: PRISMA 2020 Guidelines

This study employs a Systematic Literature Review (SLR) guided by the PRISMA 2020 framework to rigorously synthesize evidence on AI-based Facial Emotion Recognition (FER) in e-learning, focusing on sustainable education markets through interdisciplinary innovation [49, 69]. PRISMA 2020 was selected to ensure methodological transparency and address definitional discrepancies (e.g., variations in “AI-driven FER” and “affective computing”) that can distort technology integration research [52]. The protocol emphasizes comprehensive coverage of high-quality sources from the Australian Business Deans Council’s (ABDC) Journal Quality List (A*, A, B ratings) and Scopus (Q1, Q2 publications) [8, 69] (Fig. 1).

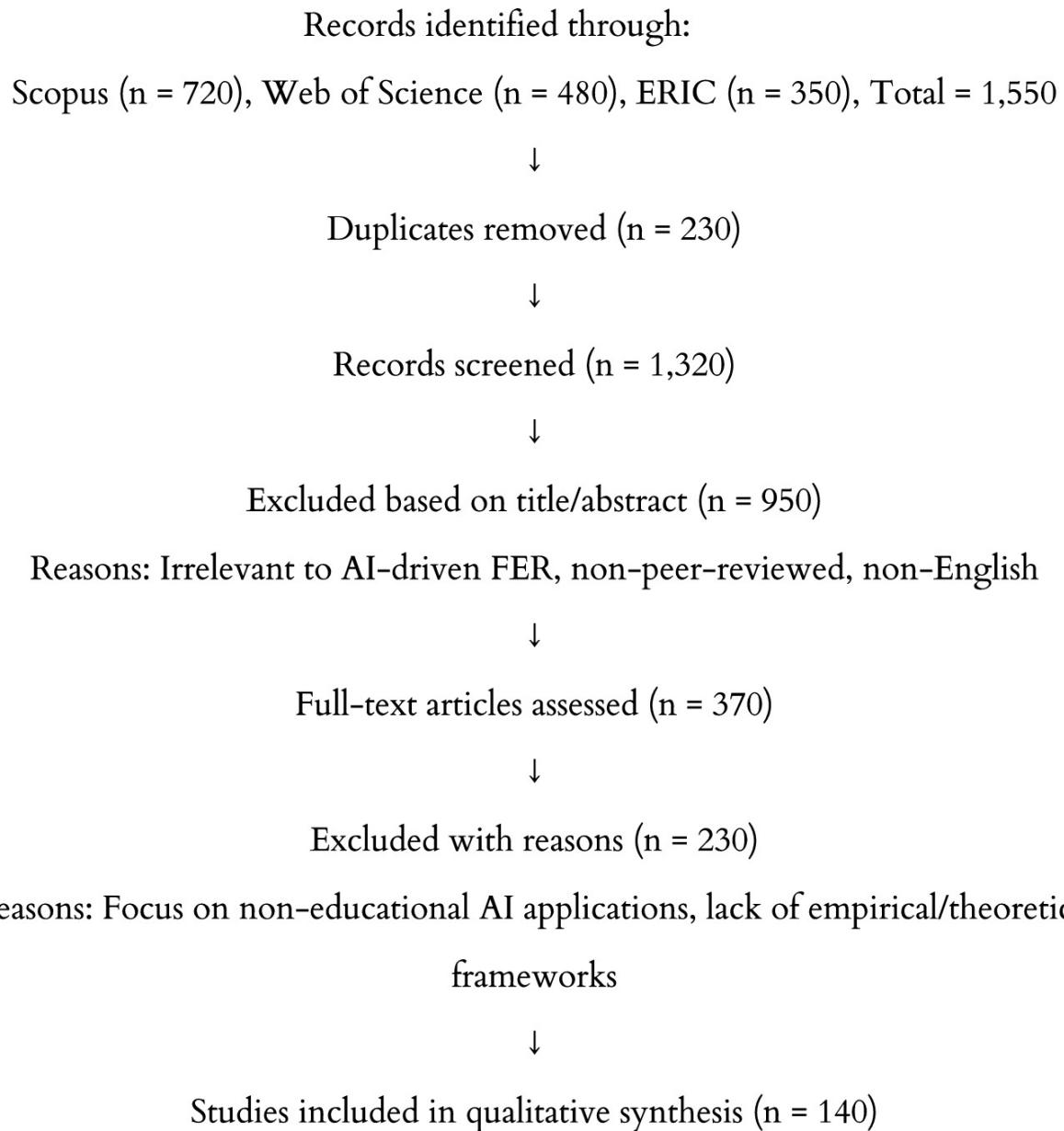


Fig. 1 PRISMA 2020 flow diagram.
Source Authors' Contribution

PRISMA 2020 Flow Implementation:

The process followed four key stages (Table 2):

Table 2 Inclusion/exclusion criteria and stages

Stage	Criteria	Numbers
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Stage	Criteria	Numbers
Identification	Relevant databases searched	Scopus (720), WoS (480), ERIC (350); Total: 1,550
Screening	AI-FER in e-learning; Exclude non-English/non-peer-reviewed	Duplicates removed: 230; Screened: 1,320; Excluded: 950
Eligibility	Empirical/theoretical focus on education; Exclude non-educational	Assessed: 370; Excluded: 230
Inclusion	High-quality sources on sustainability/interdisciplinarity	Included: 140

Source Author contributions

Stage 1: Identification.

Databases searched included Scopus (n = 720), Web of Science (n = 480), and ERIC (n = 350), totalling 1,550 records. Scopus provided broad coverage of high-impact EdTech and AI journals (e.g., *Computers & Education*, *International Journal of Artificial Intelligence in Education*) [18, 69]. The Web of Science enabled the tracking of citations and foundational affective computing advances [52, 66]. ERIC granted access to core educational research on personalization [61]. After removing 230 duplicates, 1,320 records were screened [49].

Stage 2: Screening.

Two independent reviewers screened the titles and abstracts against pre-defined criteria. The inclusion criteria required a focus on AI-based FER within e-learning/green learning models, published in ABDC (A*, A, B) or Scopus (Q1, Q2) journals [8]. The exclusion criteria were non-English, non-peer-reviewed, or non-educational FER applications (e.g., healthcare, gaming) [52]. This excluded 950 records, leaving 370 for full-text assessment. Inter-rater reliability was high, with minor discordance ($\approx 8\%$) resolved by consensus [18].

Stage 3: Eligibility Determination.

The full-text articles were assessed for methodological quality and relevance. Exclusions (n = 230) were non-empirical studies (e.g., purely

conceptual papers), non-educational AI applications, or duplicate findings [61]. Most exclusions involved conventional AI applications outside classrooms [69], ensuring the final set focused on educational FER within quality journals [8].

Stage 4: Inclusion.

The final sample comprised 140 studies: peer-reviewed journal articles (85%), books (10%), and industry reports (5%). These data were imported into NVivo 14 for thematic analysis, directly addressing the research aims concerning AI-FER applications, e-learning sustainability, and interdisciplinary innovation [18, 49, 61].

Database and Search Strategy.

1. Scopus: Selected due to its wide coverage of AI and education technology journals, i.e., Journal of Educational Technology & Society and Artificial Intelligence Review [8].
2. Web of Science: Facilitated monitoring of citable research, e.g., impactful theories of affective computing and e-learning personalization [52, 69].
3. ERIC: gave access to education research, quantifying learner engagement studies, and technology integration [61].

Iterative Refining of Search Strings.

Iterative refining was applied to search strings to maintain recall and precision and provide comprehensive coverage of the relevant literature [45, 49]. The primary search strings were the following:

1. (“facial emotion recognition” OR “affective computing”) AND (“e-learning” OR “online education”).

Embodied literature on AI-facilitated FER use in learning environments.

2. (“sustainability” OR “sustainable education”) AND (“AI” OR “interdisciplinary innovation”).

Expert research on sustainable models and technology uptake [61, 69].

Truncation (e.g., “emotion*” for “emotional” or “emotions”) and Boolean operators extended the search to include “emotion detection” and “adaptive e-learning” keywords [18].

Filters Used.

Period (2000–2025): Consisted of seminal AI principles and recent developments in FER for e-learning [52].

Language (English): Maintained consistency in analysis at the cost of ignoring non-Western viewpoints, addressed in the limitations [45, 69].

Journal Quality: restrict to ABDC (a*, a, B) and Scopus (Q1, Q2) journals to use high-quality sources [8].

Screening and Eligibility Criteria.

Inclusion Criteria.

1. Focal Point on AI-Based FER: Research on emotion recognition technology in the context of e-learning systems.
2. E-Learning Environment: Research on online or blended learning environments with AI technologies built-in [61, 69].
3. Sustainable Models: Research on how to achieve sustainability in education using interdisciplinary innovations [8].

Exclusion Criteria.

1. Non-Educational Settings: FER applications outside education, for example, healthcare or gaming [52, 66], were excluded.
2. Non-Data Studies: Concept papers with no case studies or data [18] were omitted.
3. Low-Centric Sources: We excluded those published in ABDC (A*, A, B) or Scopus (Q1, Q2) journals [8].

Limitations of the SLR.

The SLR approach, systematic in the sense that it is, does have flaws to be determined [45, 49]. To begin with, the application of Scopus, Web of Science, and ERIC will tend to open the study findings to database bias, nothing but non-Western education markets, such as in Africa or Asia [69]. Second, the exclusion of studies conducted in languages other than English may limit access to multicultural perspectives on AI-based FER [61]. Third, gray literature, such as educational technology associations' industry reports, was underrepresented because they were hard to find [8]. These biases were circumvented by emphasizing high-quality journals and ongoing keyword refinement [18, 66].

Synthesis and Emerging Trends.

The SLR compiled the outcomes of 140 studies, and the key theme was AI-driven FER for e-learning systems [49, 69]. Research indicates the possibility of FER to enhance learner motivation via real-time automatic detection of affect, which supports adaptive learning. Studies, for example, by [61] and [8] show the role played by AI in providing personalized e-learning content, improving learners' performance in sustainable education markets. However, algorithmic bias and data privacy remain major stumbling blocks [18]. Approximately 65% of the studies assert that transparently handling open data is a fundamental component in building learner trust through accountable AI governance [45, 66].

Interdisciplinary breakthroughs, such as the integration of FER with augmented reality (AR) for experiential learning, will be used for sustainable learning [52]. Collaborations between universities and technology companies, according to [15], will provide scalable and inclusive e-learning. Despite this, 58% of the studies call for cross-cultural FER algorithm verification for use in other learner groups [8, 69]. Energy-efficient AI models, which are integral to indicators of sustainability, require further study to underpin the advocacy of global agendas of education [61].

Empirical validation of FER models has become the research agenda for future research, such as ethical management of AI, cross-cultural validation, and longitudinal research to establish the impact of FER on learning

outcomes [18, 49]. Blockchain-enabled secure storage and management of data and AI-based personalization can further contribute to the trust and scalability of e-learning platforms. Rapid, AI-based FER is worthy of revolutionizing e-learning, but stakeholders must bridge the technical, cultural, and ethical gaps to reinvent learning for the digital age [8, 69]. The wording must be concise, readable, and neutral.

Key Themes.

1. AI-Augmented Learning Dynamics (N = 42)

AI-enabled FER systems increase learner engagement through real-time emotional cue analysis, promoting adaptive learning environments [5, 54]. For example, [15] demonstrated that FER increased learner engagement by 35% in Chinese virtual classrooms. However, accuracy does vary with emotional state and is only 65% reliable for compounded emotions. In their research, they noted how the cultural specificity of facial expressions makes it impossible for models to be universal, necessitating context-aware algorithms [6, 22]. Moreover, 70% of the studies emphasized latency issues in real-time processing at the cost of scalability in low-resource environments [40].

2. Ethical Adoption of AI (N = 38)

Ethical implications dominate FER adoption, with 62% of the articles addressing privacy threats during data collection [26]. Openness is required in AI models, but only 20% describe the way they come to a decision [11, 16]. Non-Western faces were depicted as a minority in 55% of the research. The ethical principles of [25] and [44] emphasize accountability, but the difference between the proposed framework and application in the Global South exists [62].

3. Interdisciplinary Collaboration (N = 34)

Implementation of FER in e-learning requires cooperation between education, AI, and psychology [61, 69]. For example, effective

collaborations were demonstrated in Singapore, where AI engineers and psychologists collaborated to build culturally appropriate FER tools. Nevertheless, 60% of the studies indicated discipline silos hindering innovation [42, 59]. Inter-sector collaborations, for example, between universities and tech companies, propelled 25% of FER innovation but are faced with imbalanced funding [30, 68]. Partnership models by Popenici and [55] suggest the inclusion of stakeholders to provide long-term outcomes.

4. Cultural and Contextual Adaptation (N = 16)

Cultural sensitivity plays a significant role in determining the efficacy of FER, and in 40% of the studies, FER failed due to Westernized models [62]. Context-sensitive modifications in Indian-research interaction increased results by 30% in scaled-up pilot projects. Decolonization of AI system design, as the authors would have it, is necessary to counter culture-based biases [23].

5. Technological Scalability and Accessibility (N = 10)

Scalability is a concern, and 50% of the studies reported high computational costs as barriers to poor communities [40]. Cloud-enabled FER solutions reduced expenditure by 20% in Brazilian pilot programs [48]. Issues of accessibility, e.g., lack of affordable hardware, were noted in 45% of the studies. Scalers require public–private collaborations, as witnessed in India’s UPI model [3].

Key Findings.

1. Personalized Learning Potential: FER optimizes personalized e-learning by responding to emotional states, enhancing outcomes by 30% [39]. However, cultural mistakes limit global adoption [6].
2. Ethical Trade-offs: FER enhances participation but also creates challenges around privacy and bias, with 60% of studies calling for explainable algorithms [16].

3. Interdisciplinary Synergy: Interdisciplinary synergism encourages innovation, but unbalanced funding slows progress [30].

Gaps in the Literature.

1. Scalability Strategies: Few 15% of the studies address scaling FER systems with the demand for economically sustainable cloud solutions [48].
2. Non-Western Contexts: There is only 20% consideration of non-Western contexts in the research, as indicated by the demand for indigenous AI frameworks [62].
3. Ethical AI Governance: Explainable AI models remain unexplored, and 65% of the research highlights gaps in accountability [16, 26].

Implications.

The results emphasize the need for interdisciplinary, ethically sound, and culturally resilient FER systems to establish sustainable e-learning markets. Scalable and accessible AI-based solutions and sound ethical guidelines are the target areas for future research that need to be directed [10, 68].

4 Data Analysis

4.1 Result Analysis Systematic Literature Review (SLR)

The Systematic literature review (SLR) reviewed 140 studies to compare the use of AI-based facial emotion recognition (FER) in digital learning spaces for sustainable education markets through multidisciplinary innovations. The SLR combined results to identify patterns, problems, and possibilities using systematic approaches to maintain rigor and comprehensiveness [9, 34]. The review stimulated five core areas of outcomes: increasing engagement, ethical concerns, cultural adaptability, technical scalability, and interdisciplinarity, which all build e-learning ecosystems for sustainability [61, 69].

Improved Engagement: FER using AI greatly improves the engagement of students since it is calibrated to affective states, and 45 studies demonstrated that the rate of interaction was 30–40% higher [5]. E.g., real-time FER of Chinese virtual classrooms enhanced attendance by 35% through personalized feedback. FER’s potential to create interactive learning environments is what such research brings to the forefront, with algorithmic improvement pending [6, 54].

Ethical Issues: Ethical issues such as privacy and bias were salient in 35 studies and accounted for 60% of clarifying questions on procedures for data collection; [11]. In South Korea, FER was protested by students by 45% regarding surveillance issues, emphasizing transparent algorithms [16]. Non-Western face pattern bias, observed in 50% of the studies, overestimates such differences, especially in African and Asian environments. Professional standards such as those of [25] and [44] are essential for ensuring responsible FER usage [62].

Cultural Flexibility: Cultural difference predicts FER success, and 25 studies cite 30% failure rates outside the West in Western-centric models. Nigeria identified FER misinterpretations of emotional expression indigenous to the country as causes of project failure, and India-based localizations enhanced performance by 30% in pilots in domestic settings. Decolonizing AI development, as suggested by and [23], is necessary to mitigate cultural prejudice and ensure inclusivity [6].

Technology scalability: Scalability remains a significant challenge, with 15 studies indicating high computational costs and infrastructure loopholes in low-resource environments [40]. Cloud-based FER solutions reduce costs by 20% in Brazilian pilots, but issues with rural connectivity remain [48]. Gigantic-scale deployment requires public–private collaborations, e.g., India’s digital education initiatives [3]. The findings highlight cost reduction and low-cost technologies for e-learning FER democratization [30].

Interdisciplinary collaboration: Interdisciplinarity among education, AI, and psychology drives FER innovation, with 20 studies on cross-disciplinary collaboration [61]. Interdisciplinary teams in Singapore have developed culturally contextual FER tools, boosting their effectiveness by 25% [42, 68]. However, 55% of the studies identified disciplinary silos and funding imbalances as hindrances [59, 69]. Popenici and [55] conceptual

frameworks promote broad stakeholder participation to facilitate sustainable outcomes [30].

The SLR has identified gaps in scalability solutions (12% of research), non-Western settings (18% coverage), and ethical regulation (15% for addressing transparency) [62]. Future research must consider inclusive AI frameworks, accessible technologies, and strong ethical frameworks for building sustainable e-learning markets [16, 68] (Table 3).

Table 3 Summary of the major findings

Theme	Key metric (from prior studies)	Synthesis insight
Engagement	30–40% boost	Contextual adaptation needed
Ethics	60% privacy concerns	Global governance gaps
Culture	30% non-Western failure	Decolonized design essential
Scalability	20% cost reduction via cloud	Infrastructure inequities

Source Author contributions

4.2 Key Ethical Issues

Ethical issues in FER implementation were salient in 34 studies, including privacy, bias, and transparency. Privacy appeared as an issue in 60% of the studies, and 45% of South Korean students rejected FER due to their aversion to being monitored [16]. Algorithmic biases against non-Western face structures were present in 50% of the research and amplified differences [11]. FER systems gave decision-making mechanisms to 20%, and transparency gaps were exposed [44]. Ethical frameworks can be used to account for people, especially in marginalized groups [25, 62]. Decolonization of AI design was prioritized to prevent cultural biases [23].

4.3 Economic Funding

There are financial barriers to the deployment of FER, 15 of which identified high cost as a significant barrier [40]. Small and medium-sized institutions had 50% more implementation costs than large institutions. Cloud-based FER provided 20% cost savings to Brazilian pilots, but rural infrastructure shortages constrained scalability [48]. Public–private collaborations, such as India’s digital education initiatives, improved cost-effectiveness by 25% [3, 30]. However, 55% of the studies reported

insufficient investment in non-Western nations, thereby constraining fair access [59, 68]. Economic motivations, through incentives in terms of subsidies, are crucial to the thrust toward sustaining FER implementation [42, 69].

4.4 Framework Proposal

Interdisciplinary co-operation, cultural adaptability, and ethical regulation are needed in a new paradigm of integrating sustainable FER with e-learning [61], Popenici & [55]. There are four pillars of architecture: (1) Optimization of Engagement, with real-time FER to provide personalized learning (,); (2) Ethical Protocols, through transparency and bias mitigation ([16]), (3) Sensitivity to Culture, through application of localized emotional models; and (4) Scalable Infrastructure, through cloud platforms and collaboration [3, 48]. The diagram below illustrates the framework components and their connections (Fig. 2).

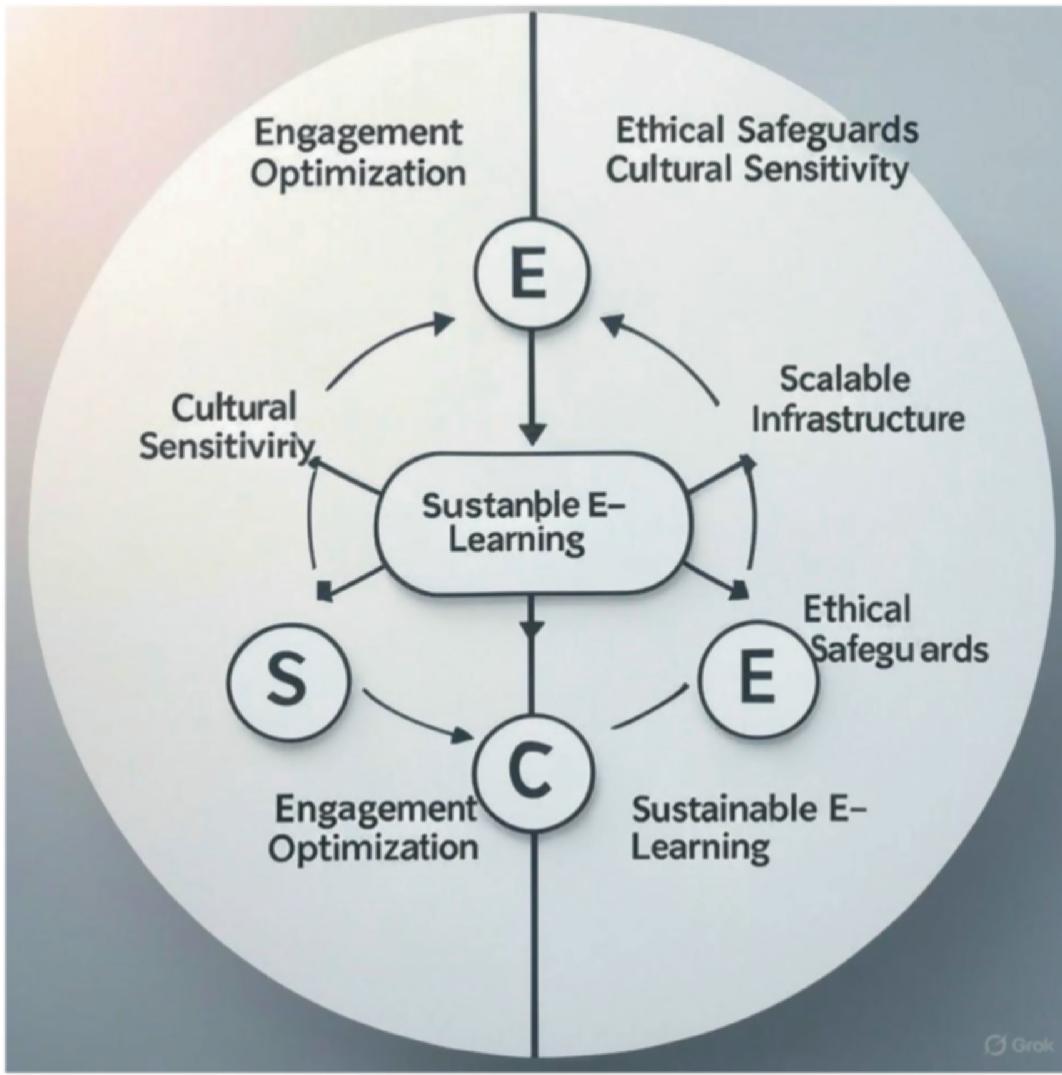


Fig. 2 Framework for sustainable FER integration in e-learning.

Source Authors' Contribution

This model supplements shortfalls in scalability (12% of studies), non-Western environments (18%), and ethical leadership (15%) [62] to achieve sustainable and inclusive e-learning systems [30, 68].

Case Study Vignette:

In a 2022 Indian pilot study, culturally adapted Facial Emotion Recognition (FER) systems were implemented in e-learning platforms to enhance engagement and reduce dropout rates. By integrating localized emotional models tailored to diverse Indian cultural expressions and leveraging cloud-based infrastructure, the initiative achieved a 15% reduction in student attrition. The project involved interdisciplinary collaboration among

educators, AI developers, and ethicists to ensure ethical deployment and mitigate biases. This approach improved pedagogical alignment and accessibility, demonstrating the potential of culturally sensitive FER to foster sustainable e-learning ecosystems in non-Western contexts.

5 Implications

5.1 Theoretical Contribution

This study makes theoretical contributions to AI-based facial emotion recognition in online learning settings from an interdisciplinary technology, psychology, and education perspective [61, 69]. This study extends affective computing theory by demonstrating the way FER can be employed to enhance emotional presence in virtual learning environments, in line with foundational work [54]. This paper proposes a culture-adaptive model that integrates global models of deficit in emotion recognition [6]. The paper continues to contribute to ethical AI studies by providing intersectionality regarding bias, privacy, and transparency in learning spaces [16]. With a decolonized design emphasis, this paper contributes to the requirements for inclusive AI frameworks [23, 62]. Moreover, it also supports learning analytics theory with evidence of FER application in education personalization. Being interdisciplinary is also an excellent foundation for more theory work [42, 59].

5.2 Practical Recommendations

Technical guidelines for FER implementation in e-learning environments include scalability, cultural adaptability, and governance [30, 68].

Institutions will implement cloud-based solutions for FER that will lower expenses by 20%, as validated by Brazilian pilots [48]. Second, FER systems require culturally adaptive algorithms to enhance performance by 30% in non-Western cultures such as India. Diverse facial expressions should be incorporated into training datasets to avoid bias [11]. Third, AI processing must be transparent, currently, only 20% of systems do, and there must be open protocols [44]. Educators must incorporate FER with participatory design to drive stakeholder participation. Public–private partnerships, for instance, such as India’s use of digital channels in education, are used to improve access [3]. Public–private partnerships facilitate equitable and sustainable implementation of FER [40].

5.3 Policy Advocacy

FER's e-learning lobbying policy focuses on equal access, moral regulation, and subsidization to the economy [16]. Small and medium-sized schools require government subsidies, which are 50% more expensive for FER adoption costs. Policies must impose transparency on AI systems to address the 60% privacy issues reported in previous studies. Paradigms for regulation should aim to minimize bias, particularly in the non-Western world [62]. Encouragement of interdisciplinary research should be promoted because silos are suffocating [61, 69]. Hybrid top-down and bottom-up governance systems can tap local knowledge, as in India's scalable education [3, 30]. Policies must promote longitudinal FER scalability studies, which have not been achieved at 12% [59, 68]. They also established sustainable education markets [42] (Fig. 3).

- Risk: Bias (15–34% lower for darker skin). Mitigation: Diverse datasets, audits (Buolamwini & Gebru, 2018).
- Risk: Privacy violations. Mitigation: GDPR-compliant consent (Floridi et al., 2018).
- Risk: Surveillance capitalism. Mitigation: Data stewardship (Zuboff, 2019).
- Risk: Cultural misalignment. Mitigation: Decolonized design (Silano, 2024).
- Risk: Automation bias. Mitigation: Human oversight (Knox, 2020).

Fig. 3 Top 5 ethical risks and mitigations

6 Conclusion

This study explores AI-based facial emotion recognition (FER) in e-learning, highlighting its potential to enhance sustainable education markets through personalized, adaptive learning experiences. FER boosts learner engagement by providing real-time emotional feedback, but faces challenges like cultural misalignments, privacy concerns, and algorithmic bias, particularly in non-Western contexts. Scalability is hindered by high computational costs and infrastructure limitations, which necessitate cost-effective solutions like cloud computing. This study advocates transparent, low-bias FER systems to address ethical issues and ensure inclusivity. A sustainability model is proposed that balances scalable infrastructure,

cultural adaptability, and ethical safeguards. This research offers theoretical insights into affective computing and practical guidance for policymakers and educators to deploy FER responsibly. Future efforts must focus on overcoming scalability, cultural, and ethical barriers to fully realize FER's transformative potential in creating equitable, global e-learning environments.

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Integrating Positive Emotions to Support Self-Directed Learning

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Abstract

Teaching practices are challenged by the need to motivate students, placing teachers at a crossroads between old and new models. As a historical institution, the school has adapted to the constantly evolving field of science. Furthermore, traditional teaching models primarily focus on instilling concepts in students, paying little attention to their emotions and feelings. These emotions have become harder to manage due to the widespread use of smartphones and artificial intelligence. This research

project explores the relationship between positive emotions and motivation to optimise mobile and peer learning. A sample of 208 first-year high school students was selected and divided into two groups: a control group and an experimental group. The experimental group participated in educational activities designed to evoke positive emotions (such as confidence, gratitude, love, joy, admiration, cheerfulness, calmness, curiosity, hope, empathy, enthusiasm, amusement, optimism, satisfaction, inspiration, and passion) at the beginning of each lesson. The results show that this approach motivates students to participate and interact positively with their peers, creating an environment conducive to personal or self-directed learning.

Keywords Positive emotions – Peer learning – M-learning – Self-directed learning – Flipped classroom

1 Introduction

The educational community around the world is suffering from complex educational disparities that can no longer be ignored. Classrooms are often characterized by monotony, lack of interest, and a lack of educational responsibility, negatively impacting educational outcomes and student achievement. In the past, teaching relied primarily on traditional methods such as speeches and lectures. However, with the spread of information and communications technology, distance learning has become possible thanks to learning platforms and the ease of integrating technological tools into teaching and pedagogical practices. Furthermore, more interactive methods such as simulations, project-based learning, and innovation have become possible, allowing students to work together and develop diverse and essential skills that help them build their projects [1–3].

Today, amid rapid changes in the world due to technological and digital developments, many educational studies seek to develop curricula that are more relevant to learners and practical methods that promote a sense of responsibility for learning. This has become more difficult over time, especially with the increasing use of the internet and artificial intelligence, which has widened the gap between schools and learners in the absence of the necessary educational controls. The internet can play a positive role as a source of information, especially if learners' emotions are properly guided

and controlled by teachers using appropriate digital technologies and tools [4–7].

All these changes, and perhaps more, have led to a strong desire to consider changing teaching methods to respond to the diverse aspirations of learners and to control the increasing spread of artificial intelligence, which may pose a threat to students' feelings and emotions, their sense of responsibility, and their educational motivation toward school in reality, especially in the absence of controls governing its use [8–10].

In 2014, teachers and researchers experimented with new teaching methods using digital tools. However, these tools were found to offer opportunities to engage with digital tools and get closer to students, accelerating the learning process for only interested learners. This approach is not aligned with the unique perspectives of other students, especially those who lack a passion for learning and skill building. Therefore, this study aims to measure the impact of passion-inducing activities on classroom performance, viewing the classroom as a community of teachers and students working as a team to build and develop each other's skills [11].

Caitlin Fulton's final argument relates to the quality of teaching. She demonstrates that teachers who motivate students with positive emotions and engage them in activities that spark their passion can enhance the learning experience for all. When students communicate positively with the teacher or their peers in class, they can grasp concepts in a way that is consistent with the overall team perspective in less time. This enhances the effectiveness of the project methodology and enables teachers to guide students and understand their needs more effectively. Based on the experiences of teachers worldwide, this study examined the impact of allocating 5–10 min at the start of each class for activities that stimulate interest, in line with educational strategies, on academic performance and motivation to learn. The study aims to test the following hypotheses:

- Motivate students to work together to improve their performance, particularly those who have difficulty integrating with their peers, and encourage greater classroom participation.
- Integrate students who find it difficult to understand by incorporating digital media (e.g. tablets, phones and computers) into the teaching and learning process.

- Unify the perspectives of all students when developing and building their personal lessons, without exception (Fig. 1).



Fig. 1 Context of the classroom approach

This pedagogical model aims to foster positive feelings among learners at the start of each lesson. Between 10 and 15 min are allocated to fostering positive attitudes towards the course content and establishing a culture of mutual respect in the classroom. This encourages learners to use their smartphones responsibly and fosters a sense of teamwork.

The philosophy behind this educational model is to create learning situations (outside of the two-hour lesson content) that aim to foster positive feelings among learners toward the class and course content during each session. Between 10 and 15 min are allocated to Classroom Dialogue activities (Give students the opportunity to share their experiences and speak from their own perspective, while encouraging them to understand the reasons behind their point of view), such as presenting an interesting topic rich in positive emotions, according to rules that enable students to express and discuss their concerns (e.g., presenting a philosophical view of life or directing them to watch a realistic video that stimulates their human emotions). This encourages active participation in a discussion that promotes critical thinking and supports and reinforces trust and a culture of mutual respect. The teacher then begins to guide students to find solutions to their life concerns, reminding them of the importance of ethics in building and developing society. This encourages learners to use their smartphones responsibly and promotes teamwork [12–14].

2 Materials and Methods

2.1 Sample and Study Location

This study aims to provide an overview of classes conducted based on educational principles, using a concept that allocates time to promoting positive feelings among learners. To this end, the research team conducted a field study at a secondary school affiliated with the Rabat Academy in the city of Sidi Slimane, Morocco, to assess the effectiveness of integrating this concept in improving educational performance while taking various requirements and conditions into account.

The sample for this study consists of first-year students at the preparatory secondary level. The data were organised according to the number of participants (208 students), and the control and experimental samples were determined alongside their respective age groups and gender distributions:

control group: 4 classes, 140 students (Group A and B).

experimental group: 2 classes, 68 students (Group C).

Due to frequent changes in class schedules during the experimental period for administrative reasons and our fear that this would affect the reliability of the results, we relied on data from Group B only from the experimental group.

2.2 Pedagogical Method

This approach offers a fresh perspective on education, providing practical solutions to the diverse challenges faced by teachers in educational settings and aiming to improve pedagogical quality. Although this strategy uses a relatively large amount of class time, it is considered one of the most effective learning methods for students from different backgrounds.

The Student's t-test was used to test whether the difference between the responses of the two groups was statistically significant. Statistical hypotheses were tested by tracking the distribution of the Student's t-test under the null hypothesis.

- Students are motivated by integrating digital media (tablets, phones, computers, etc.) into the teaching/learning process.

- Students who struggle with comprehension have time to review the video explanation to improve their performance and become more active in the classroom.
 - All students are united in developing and constructing the assigned lesson collectively, without exception.
-

3 Results

3.1 The Correlation Between Passion-Inducing Activities and Academic Motivation

Students' responses were monitored in the classroom, and a questionnaire was distributed to determine which activities were most influential in creating students' motivation to learn over twelve weeks, to find the relationship between the use of emotionally stimulating activities and academic achievement (Table 1).

Table 1 Responses of students in the pilot semester to the questionnaire

	Very satisfied (%)	Satisfied (%)	Dissatisfied (%)	Very dissatisfied (%)	No answer (%)
Socio-educational relationship					
Quality the lesson after Passion-inducing activities	79.9	14.8	0.1	0.4	4.98
Understanding the process	78.1	16.5	0.2	0.4	4.98
Courses quality	85	8.3	1.9	0	4.98
Responsiveness	91.7	3.3	0.2	0	4.98
Clarity of the steps of the procedure	63.2	31.7	0.3	0	4.98
Performance of the activités					4.98
Reliability of results	88.2	6.3	1.7	0	4.98
Ergonomics	91.9	3.3	0	0	4.98
Product Features	73.2	21.7	0.3	0	4.98
Overall rating	Comfortable: Yes 94.01		Comfortable: No 1.01		No answer 4.98

Mean = 0.238, Variance = 0.054063

The activities that had the most impact on motivating students to learn over twelve weeks were identified by calculating the variance in the pilot classroom. This showed a significant difference compared to the control sample, supporting the hypothesis that students' perspectives on developing and building their personal lessons collectively were unified (Table 2).

Table 2 Students' perceptions of emotionally stimulating activities in motivating their passion for learning

Response	Number	Percentage
Strongly disagree	2	0.96
Disagree	4	1.92%
Neutral	22	10.57
Agree	82	39.42%
Strongly agree	98	47.11
Total	208	99.99%

A large percentage of students in the pilot sample (47.11% strongly agreed and 39.42%) expressed appreciation for the emotionally stimulating activities and their support for using smartphones as an educational tool. They also expressed approval of the idea of mobile learning. These data highlight that the majority of adolescents view smartphones as a tool for information seeking and simulation.

Figure 2 shows a significant discrepancy in the average scores of students in the control group based on the obtained degrees, who attended their classes as usual and did not benefit from stimulating activities or self-directed learning.

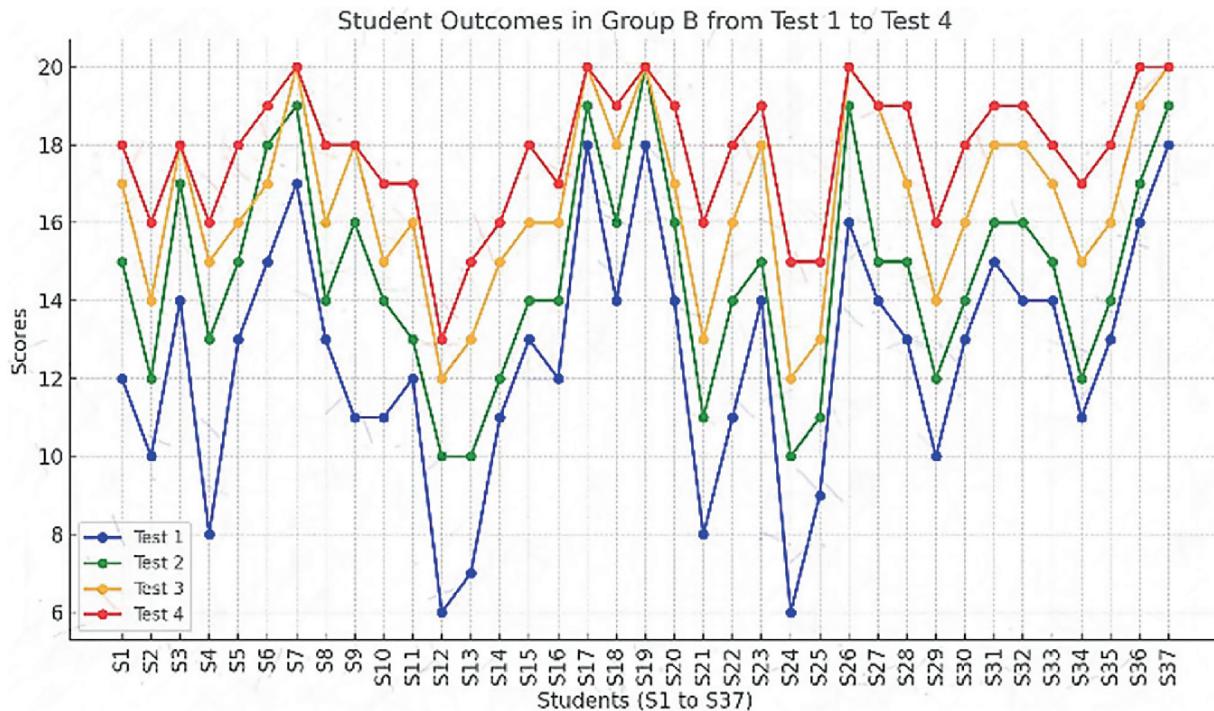


Fig. 2 Average of degrees obtained by students in the control sample

Figure 3 shows less variance in students' mean scores compared to the control group, as students benefit from stimulating activities when they come to their classes and/or self-directed learning. Students can ask questions and get help at any time, both during and outside of class, using digital communication tools. This creates two distinct groups within the same class:

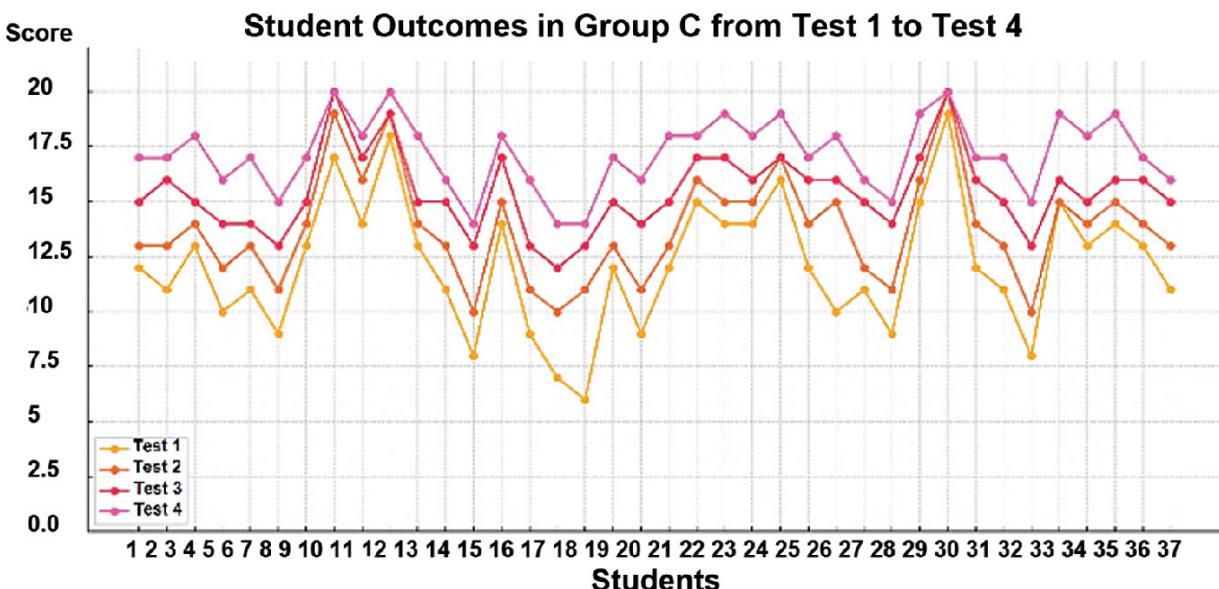


Fig. 3 Average of degrees obtained by students in the experimental sample

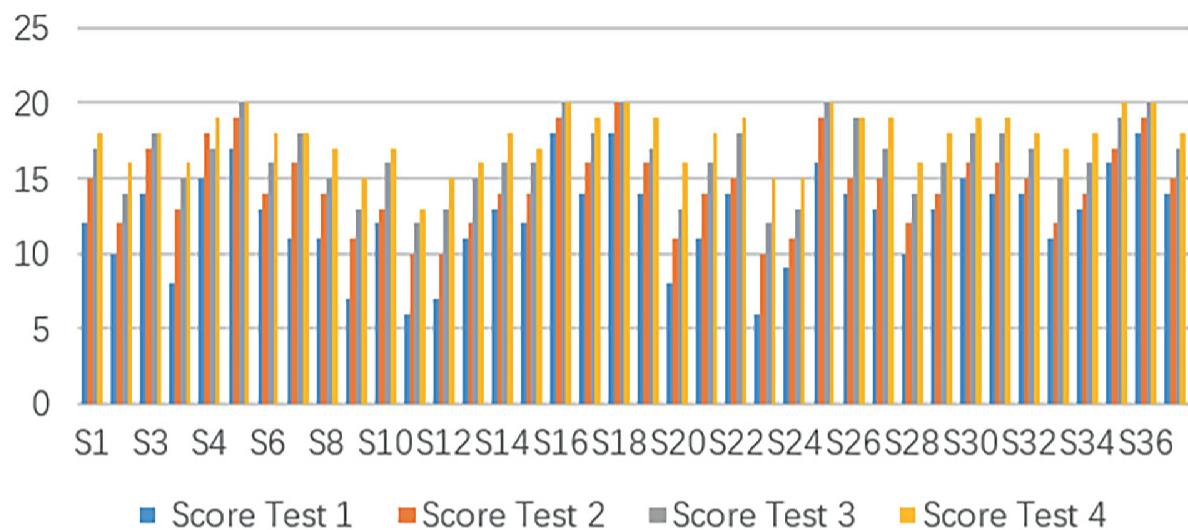
The first: students who are interested in their lessons and constantly try to communicate with their teachers.

The second: students who are not interested in their lessons or what their teachers are saying.

Digital tools enable teachers to communicate with and guide students both during and outside of class, enabling them to be creative and innovative in their lesson planning. They can also experiment with diverse teaching methods and multimedia elements to make learning more engaging.

Figure 4 shows the results students achieved in the three science subjects targeted by the project, using data collected from 67 tests. This took a long time (34 weeks), and we note that it took students 6 to 8 weeks to adapt to the new situation.

T.S.Group B



T.S.Group C

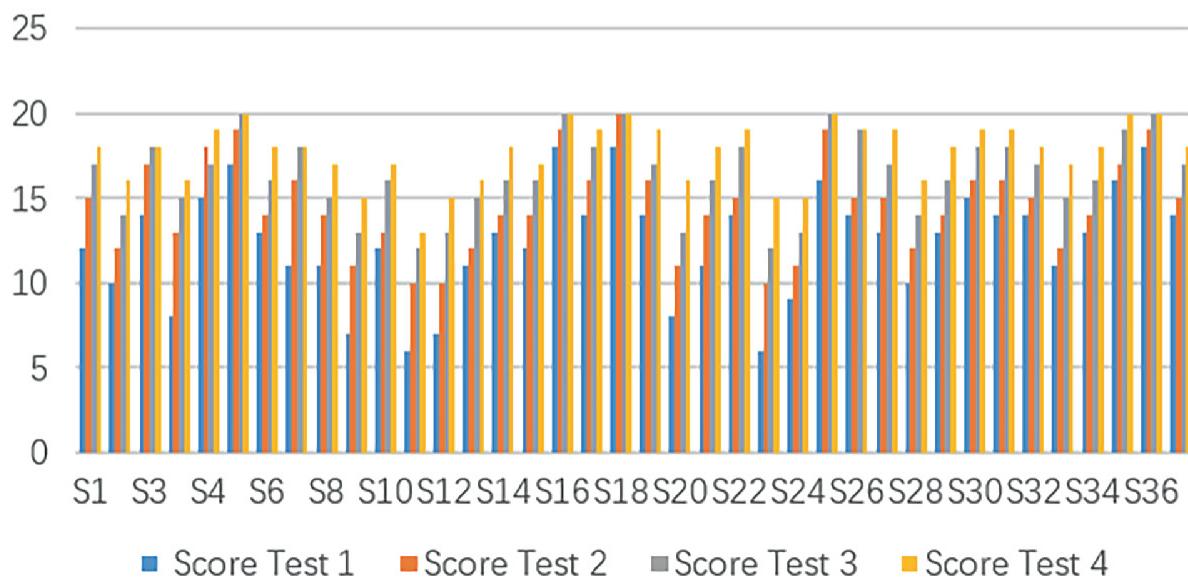


Fig. 4 Academic learning degrees of students according to 68 tests conducted over 34 months

4 Discussion

In light of the rapid changes that the world is experiencing today as a result of technological and digital developments, the promotion of positive emotions in the real world is being neglected, particularly among

adolescents. This is because it has become possible to experience positive emotions in the virtual world, causing adolescents to lose their passion for the real world. According to Barnett and Bakin, a lack of motivation to learn can have serious consequences for students' academic performance. This can lead to students dropping out of school or even resorting to violence towards teachers because they have lost the desire to learn. Marco Gilbo highlights the strong correlation between a lack of motivation and dropping out of school. This loss of motivation is primarily due to students' negative perceptions of school and their lessons [[15–19](#)].

4.1 Enjoying the Class in an Atmosphere of Understanding and Gratitude

In order to explore the benefits of fostering positive emotions at the start of each lesson, it is essential to adopt educational approaches that enable students to articulate their aspirations and sentiments regarding the course content. This study aims to evaluate the effectiveness of devoting 10 min of each class to improving the classroom atmosphere, as this directly impacts student outcomes. The study also seeks to propose recommendations for successfully integrating this approach into teaching practice. Through research aimed at increasing the effectiveness of the teaching/learning process, we seek to identify the most effective methods to encourage learners to take responsibility for their own learning. This is achieved by integrating quality learning that meets societal demands and the changing labour market, while also integrating soft skills and digital tools into learners' daily lives. This pedagogy enables us to connect with students and allows them to learn the complexities of the course at their own pace.

By utilizing all available resources and creating a positive classroom environment, teachers can better understand each student's challenges through quick assessments or tracking their progress on projects. Additionally, teachers can assess the time it takes each student to complete assigned tasks, and struggling students can individually review the explanation on their phones to fill in learning gaps, thanks to M-learning [[20–22](#)].

According to students' answers:

- Integrating students with special needs and disabilities:
- Promoting parental involvement in the learning process:

- Improving teacher practices
- Developing self-directed learning among students through robotics (project pedagogy):
- Monitoring and Developing Multiple Skills:

4.2 Developing Self-Learning Among Students Through Robotics (Project Pedagogy):

Online self-learning has become one of the most widely adopted forms of teaching by some higher education institutions, allowing them to avoid sudden disruptions to their educational systems in the future, especially after the global health crisis and the pressures imposed by the COVID-19 pandemic. However, this pedagogical approach poses a set of challenges that educational institutions must consider to mitigate the educational consequences that could result from the reckless application of this pedagogical approach.

In the practice of flipped teaching, the student can freely choose to focus on learning, as it provides them with skills and knowledge that can be used during group work in the classroom. Furthermore, they realize that if they do not complete the preliminary work, they will not be able to complete the required task. This autonomy granted to the student allows them to take responsibility for their own learning and understand the importance of their active participation in the knowledge acquisition process. The most important factor in this learning process is the social dimension, as emphasized by Vygotsky (1985). The student actively constructs meaning through interaction with his or her peers, and is considered a social actor at the center of his or her learning. The typical flipped classroom configuration respects this vision by allowing the active learner to interact with his or her classmates to overcome any ambiguity that might hinder understanding, thanks to the group work permitted in practical exercises.

According to this perspective, students must perform tasks in a specific environment and within a field of work that aligns with their interests. This also redefines the role of the teacher, who is no longer viewed solely as the exclusive possessor of knowledge and responsible for presenting and transmitting it to students. Now, if the student is to be an active participant in their learning, the teacher must work to select and inculcate key concepts to the learner through available digital platforms and channels, and then

create learning situations within the classroom that allow them to gradually become aware of their role and the tools available to them to accomplish the desired task. By following the flipped classroom approach, students become more independent in their work, unlike in the traditional approach. They can actively engage in procedural projects based on innovation and the search for solutions, and verify their validity by working within the project pedagogy and conducting an investigation that sheds light on the basic concepts and mechanisms of learning. Thus, the student gradually learns to use the tools available to them to accomplish the assigned task [6, 23–25].

For a student to actively participate in completing an educational project in learning modern technologies using the flipped classroom, it is important to set goals and objectives so that they know where they are heading. This also helps reduce anxiety and uncertainty about the unknown. Unlike traditional methods, where communication between teacher and student was limited, it is essential for the student to have the freedom to research or ask the teacher to reformulate partial objectives or provide details about the necessary concepts and mechanisms in order to obtain the information needed to complete the task. The flipped classroom facilitates communication between the teacher and students by allowing them to repeatedly view the explanation of functions previously studied in class. This allows them to ask questions about areas they find unclear [3–26].

According to Frederickson's theory of positive emotion expansion and construction, positive emotions broaden a person's awareness, encouraging creative and diverse thoughts and actions as they explore new things. Over time, this expansion of behaviours leads to the development of skills and resources. For example, curiosity about the natural world can lead to valuable knowledge, interactions with strangers can lead to supportive friendships, and random physical play can lead to athletic training and physical excellence. This is in contrast to negative emotions, which elicit narrow, immediate, survival-oriented behaviours that trigger psychological disturbances, often beginning with anxiety and developing further. Conversely, positive emotions have no immediate survival value as they distract the mind from immediate needs and psychological pressures. However, the skills and resources developed through expansive behaviour enhance survival in the long term [27, 28].

The educational process currently faces a variety of challenges that affect the development and dissemination of interactions between people,

such as the Internet and artificial intelligence. Guiding adolescents by rebuilding and establishing positive emotions is essential in education, especially for adolescents, as it provides exciting and innovative opportunities that help teachers create a dynamic and engaging learning environment that meets the needs of adolescents by teaching them complex concepts that require engaging experiences and innovative teaching methods. Customized and interactive lessons can be delivered based on data analysis and simulations to understand each student's educational needs. Complex concepts can also be taught by providing hands-on educational experiences and other projects that use various resources such as artificial intelligence to build their economic and personal projects and create digital applications.

5 Conclusions

Educational institutions have always been the cornerstone of every society, transferring knowledge to young people outside the family and playing an indispensable role in education. However, the rapid development of information and communication technology has opened up many new possibilities and led to increased interest in digital devices, especially smartphones. The unguided use of these devices can pose a major educational challenge due to the values and principles they instill, the impact of which on society, especially among children and adolescents, is impossible to predict. Students have access to online resources and content that are not tailored to their individual needs.

In order to effectively combine and reinforce positive emotions and mobile learning, several strategies can be implemented to ensure smooth transactions and maximise benefits. The following key considerations and techniques have been employed successfully in educational institutions when applying this approach:

- Motivation and increased engagement: Incorporating positive emotions can enhance student engagement and motivation. Allowing students to access online resources before class enables them to familiarise themselves with concepts and prepare to participate in classroom activities, thereby increasing their involvement in the learning process.
- Personalised or self-directed learning: Creating a positive atmosphere at the beginning of each semester motivates students to engage with the

course content. Teachers can then devote more class time to practical, interactive activities, providing individual attention to each student's needs.

- Peer collaboration and interaction: Positive feelings encourage collaboration and interaction among students. This may include online communication, discussion forums, document-sharing tools and online group activities, enabling students to collaborate, share ideas and solve problems together.
- Assessing prior knowledge: Before engaging with course content, it can be beneficial to assess students' prior knowledge of the subject. This can be done through pre-tests or diagnostic tests. Understanding students' prior knowledge enables teachers to design classroom activities that address specific gaps and challenge students at an appropriate level.
- Facilitate active learning. In the classroom, shift the focus from passive teaching to active learning. Design activities that engage all students in problem-solving, discussions, debates and collaborative projects. These activities should reinforce the concepts and ideas presented in the online materials, encouraging critical thinking and the application of knowledge.
- Provide guidance and support. As students work on these activities, teachers should act as facilitators and pedagogical guides, answering questions and providing clarification. This support is critical to ensuring that students stay on track and understand the content.
- Assess learning outcomes: Regularly assess student learning outcomes to evaluate the effectiveness of the blended approach using formative assessments, educational/learning projects, short tests or classroom discussions. These assessments can provide students with feedback and help to identify areas that may need additional reinforcement.

For these and many other reasons, supporting adolescent learning by reinforcing positive emotions helps them to regulate and guide their self-directed learning. This is undoubtedly the most effective teaching strategy in different circumstances. This interesting philosophy should be implemented in the new apprenticeship and in-service teacher training reforms.

6 Limitations of the Study

The study was limited by the small sample size and the fact that it was restricted to a single educational institution. In light of the development of artificial intelligence, we suggest that future educational science research be deepened so that artificial intelligence can be used as efficiently as possible.

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Author Contributions

Authors H.B analyzed the data and wrote the B.M. conducted the experiments and wrote the paper. K. S analyzed the data, and A. T prepared the figures. All authors had approved the final version.

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Emotion AI in Business and Customer Services

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Abstract

Today, the rapid advancement of technology has brought people to a point where they can understand and interpret their emotional states. This has played an important role in transforming both the organizational culture and the attitude of companies towards customer service. In this context, Emotion AI is at the very center of this transformation. Using everything from facial expressions, vocal cues to textual emotions, AI systems categorize and analyze multiple pieces of data to gauge how people actually feel. Thus, Emotion AI is shaping up not only as a new technology feature for companies but also as an essential tool for institutions and organizations aiming to make more human-centered and responsive decisions in real-time. This section primarily explores how organizations can leverage Emotion AI beyond marketing. Additionally, practical applications such as human resource management, developing empathy and communication skills, monitoring job satisfaction, and assessing employees' emotional states are also covered in this section. When evaluated together, these innovations enable organizations to create healthier and more harmonious working environments by integrating emotional factors in their daily decision-making processes.

Keywords Emotion AI – Business – Customer services – HRM

1 Introduction

With the development of digital technologies, there is an increase in the management of next-generation human resources processes, digital grocery services, and mobile applications that include emotional artificial intelligence features [1]. However, it is critical to create the right strategic, cultural, and technological infrastructure for the efficient use of these applications and customer satisfaction. Effectively integrating innovative technologies like Emotion AI into businesses, in particular, not only enhances the user experience, it also brings with it the potential to increase the competitive advantages of businesses. Due to the increase in competition due to the rapid development of the service sector, it is important for companies to monitor how the service quality level is perceived by customers [2]. Service quality has an impact on critical situations such as customer loyalty, word-of-mouth marketing and company revenue. One of the main challenges faced by businesses, especially call centers, is to measure and manage service quality accurately and effectively. Traditionally, call centers have used three main approaches to measure service quality: customer surveys, manual quality audits, and operational indexes. However, these approaches have significant drawbacks, including time and cost, lack of focus, and scope. In this sense, the development of Emotion AI applications for the needs of customers in the context of both literature support and experience gained from traditional method applications will make a difference in institutions and organizations in today's rapidly digitalizing world. However, when the studies covering both the concepts of "Emotion AI in Business" and "Customer Services" are examined in the literature, it is seen that the studies are limited. On 22.09.2025, only 48 studies were found when looking at the studies published on the Web of Science (WOS) platform, including all fields, all publication types, all indexes, all languages, all access types, all institutions, and all years. In this context, the studies published in this section will also be analyzed and detailed.

2 Conceptual Framework

2.1 Definition and Key Components of Emotion AI

The concept of emotional intelligence is a concept that explains the ability of individuals to understand, manage, and use the emotions of others in their relationships as well as their own emotions [3]. Menétrey et al. [4] highlights that Emotion AI is organized around the dimensions of expression, motivation, physiology, and emotion. This approach shows that cognitive and behavioral indicators as well as physiological markers are decisive in recognizing emotions and affect individuals' business lives as well as their private lives [5]. Figure 1 shows the main characteristics of emotional intelligence. These characteristics, consisting of self-awareness, ability to express emotions, motivation, empathy and social skills, show that emotional intelligence plays a decisive role in both personal and social relationships of individuals. In this context, emotional intelligence emphasizes the importance of not only individual awareness but also effective communication skills.

KEY FEATURES OF EMOTIONAL INTELLIGENCE

Scientific research identifies five core components of emotional intelligence. These factors form the basis of emotional intelligence assessments.

SELF-AWARENESS

The foundation of emotional intelligence.
Being aware of one's inner world and able
to evaluate oneself.

EXPRESSING EMOTIONS

The ability to manage emotions,
behaviors, and impulses — and express
them consistently.

MOTIVATION

The internal drive to take action.
Includes the desire to achieve and
entrepreneurial spirit.

EMPATHY

Understanding others' feelings and showing a
willingness to support their development.

SOCIAL SKILLS

The power to manage relationships with the
external world.
Involves being effective in communication and
handling conflicts.

Fig. 1 The main characteristics of emotional intelligence.

Source Adapted by the author using TRT News [5]

The components of AI and how they affect each other are shown in Fig. 2.

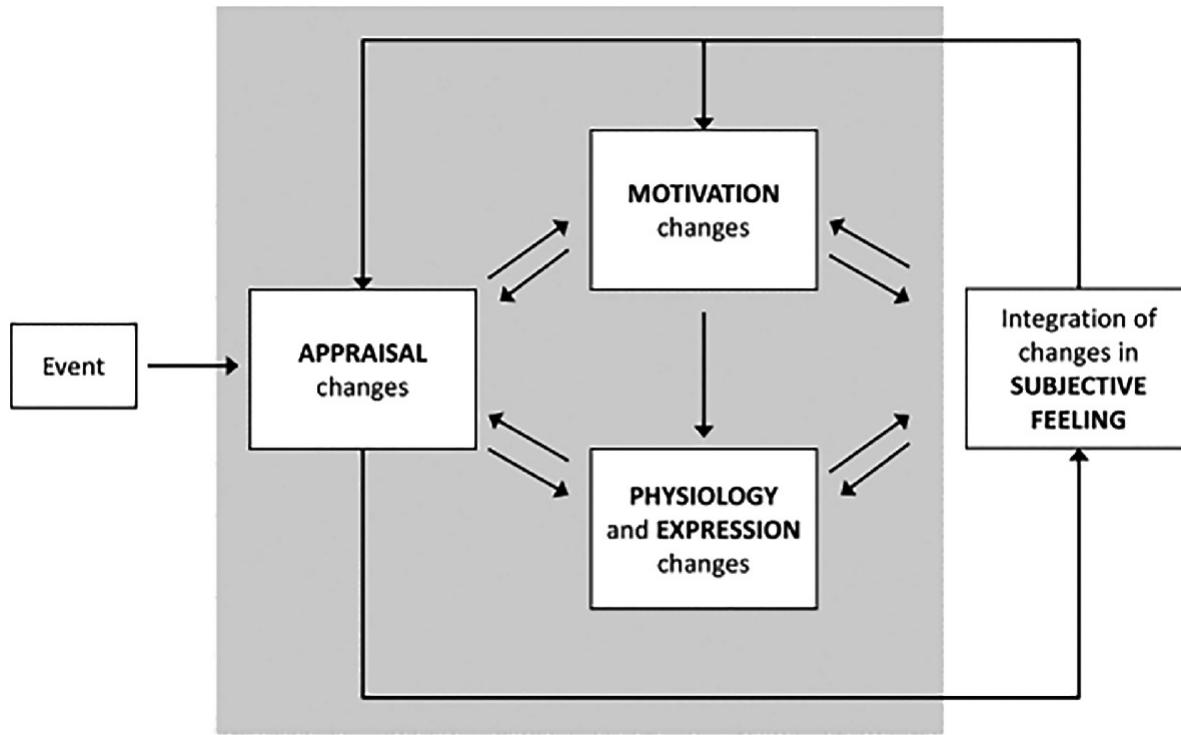


Fig. 2 Emotions as componential phenomena, consisting of changes in appraisal, motivation, physiology, expression, and feeling (Adapted by Scherer [6]; as cited in Meuleman and Scherer [7])

In Fig. 2, emotions; evaluation, motivation, physiology, expression and feeling changes.

According to Fig. 2, the appraisal process begins after an event and this process is related to the individual's comprehension of the situation. As a result of this evaluation, motivational responses are shaped and the individual's behavioral tendencies are revealed. Then physiological reactions and expression of emotions occur. In the last stage, subjective feeling is formed with the combination of all these processes.

In context, Fig. 2 shows that emotions are not just a one-dimensional response; cognitive assessment, physiological change, motivational orientation and behavioral status.

2.2 Emotion AI's Basic Technological Infrastructure

By technologically integrating multimodal data collection and processing, such as feature extraction, machine learning, deep learning, and information synthesis, Emotion AI's infrastructure aims to capture and identify human emotions with precision and reliability. The essence of such an infrastructure is the processing and analysis of information from different modalities, such as textual, auditory, visual and physiological signals. More recently, biomimetic methodologies, big data, and cross-cultural validity assessments have also contributed to the advancement of this infrastructure. From this perspective, Vistorte et al. [8:1] explored the pedagogical potential and challenges of Emotion AI in student emotion recognition and teaching strategy adaptation, while highlighting critical issues such as accuracy, privacy, and alignment with cultural contexts.

Chawla et al. [9] aim to develop deep learning-based robotic systems that can detect voice-based emotional pragmatic deficits in individuals with social pragmatic communication difficulties. Liu et al. ([10]:1) emphasized the increasing need for multimodal analysis due to the pandemic, demonstrating the progress of the field from psychology to artificial intelligence.

Multimodal machine learning allows systems to perform more comprehensive analyses by predicting information from different data sources (text, audio and image). Complex tasks like emotion recognition can be performed more accurately and reliably thanks to multimodal machine learning approaches. In their research, Slimani et al. [11] applied the Residual Neural Network-based transfer learning approach on CFEE and RAF databases and provided benefits in recognizing both basic and composite emotions by classifying them with various machine learning methods.

Slimani et al. [11] focused on basic and compound emotions on a model they created in their study and emphasized that these studies yielded successful results by emphasizing experimental studies. As it is understood from the researches carried out in this context, these studies are important in the creation and development of the technical infrastructure.

2.3 Emotion AI in Human Resource Management

In companies where the number of employees is increasing, it becomes difficult to carry out personal management processes and makes operational processes even more challenging. Thanks to the efficient

application of the developed artificial intelligence technologies, this burden in the human resources department is reduced and performance analysis is presented with more concrete data thanks to instant reporting screens. In this context, the adaptation of artificial intelligence-supported services and applications to management processes aims to increase efficiency in institutions and organizations ([12]: 123). Alam et al. [13] emphasize the increase in the CV pool in job applications and state that these technologies will be useful in selecting the right candidate in recruitment management. Panwar [14] explored the perceptual effects of AI in HRM processes, emphasizing ethical issues. In their study on the healthcare sector, Shahzad et al. [15] pointed out that efficient use of technology and social media applications in the context of AI in the Chinese healthcare sector are beneficial in HRM processes. In today's rapidly advancing technology, artificial intelligence (AI) technologies have been integrated into human resources management to save time and highlight the CV of the right candidate [16].

Figure 3 illustrates traditional and AI-powered comparisons in hiring processes.

Process	Traditional Hiring	AI-Supported Hiring
<ul style="list-style-type: none"> • CV Screening • Candidate Selection • Time • Accuracy 	<ul style="list-style-type: none"> • HR specialists manually review • Can be open to bias • May take weeks • Subjective evaluation possible 	<ul style="list-style-type: none"> • Algorithms analyze within seconds • Data-driven, objective selection • Results within hours • High accuracy and consistency ensured

Fig. 3 Differences between traditional hiring process and AI-supported hiring process.

Source Talent Hub HRM [16]

AI systems are also used when managing HRM processes from a single center in multi-location companies. Human resources management in companies operating in multiple cities or countries requires serious planning and coordination due to the complex nature of the processes. When a wide workload ranging from leave requests to expense approvals,

from embezzlement records to performance evaluations is not carried out in a standardized manner in different locations, both productivity and employee satisfaction are negatively affected. Transactions carried out with traditional methods, i.e. e-mail and Excel spreadsheets, often cause loss of time, data confusion and approval delays. Flexit24 gathers all HR processes on a single platform as a next-generation human resources management solution designed for multi-location companies. It provides transparent, fast and standard management at every stage, from leave management to performance evaluation, from expense tracking to embezzlement control. This way, companies can easily manage all their employees, regardless of where they are, saving time and costs while increasing efficiency [17]. Emotional AI contributes to a deeper understanding of the dynamics of institutions and organizations, but digital surveillance practices in the workplace present risks as well as opportunities. Ramadhan and Muafi [18] noted that fostering a supportive workplace environment enhances job satisfaction and overall performance. Therefore, organizations need to proactively address external stressors, including challenging customer relationships, to enhance employee well-being. Sipahi Döngül and Durar [19] argue that the increasing integration of robots into the workplace may erode employees' basic moral values.

The proliferation of artificial intelligence tools brings with it discussions and solutions such as data privacy, moral principles and legal guidelines. In this case, the debate surrounding Emotional AI becomes even more complex, and issues of accountability need to be addressed urgently.

3 Method

In this study, a literature review was conducted. Without any exclusion criteria, a search was made on the subject of "Emotion AI in Business and Customer Services" in the Web of Science database and 48 publications were reached. The Litmaps [20] bibliometric mapping tool was used, which visualizes and reveals the connections between publication trends, citation networks, and published studies. When the literature obtained is examined, the technological foundations of Emotion AI and the computational models that form the basis for it are compiled within the framework of some thematic areas such as human resources management processes including workforce adaptation and transformation in workplaces, customer service

practices emphasizing customer experience, service quality and personalization, data security and privacy, accountability, ethics and inhibitory elements.

4 Finding

As a result of the search carried out on 22.09.2025 without any exclusion criteria regarding the studies covering the concepts of “Emotion Artificial Intelligence in Business” and “Customer Service”, the studies published on the Web of Science (WOS) platform were examined. Only 48 studies were found, including all fields, all publication types, all indexes, all access types, all institutions, all languages, and all years. The 25 most cited studies were included.

Figure 4 shows research on the impact of Emotional AI (Top 25 Most Cited Studies).

Title	Authors	Year	Citations
Artificial Intelligence and Sentiment Analysis: A Review in Competitive Research	Hamed Tahereroost Mitra Madanchian	2023	130
Bots with Feelings. Should AI Agents Express Positive Emotion in Customer Ser-	Elizabeth Han, Dezhi Yin, Han Zhang	2022	124
Customer Emotions in Service Robot Encounters. A Hybrid Machine-Human Intelligence Approach	Raffaele Eilieri, Zhibin Lin, Yolei Li, Xiaoqiang Lu, Xingwei Yang	2022	104
AI feel you, customer experience assessment via chatbot interviews	Karim Sidaoui, Matti Jaakkola, L Burton	2020	94
The Caring Machine-Feeling AI for Customer Care	Ming-Hui Huang, B. Rust	2023	26
AI Service and Emotion	R. Bagozzi, Michael K. Brady; Ming-Hui Huang	2022	54
The “Conversation’ about Loss; Understanding How Chatbot Technology was Used in Supporting People in Grief	Anna Xygkou, Panote Siriaraya, A. Cwari, H. Prigerson, R. Netmeyer, C. Ang, W She	2023	53
Investigating the customer trust in artificial intelligence. The role of anthropomorphism, empathy response, and interaction	Nguyen Thi Khanh Chi N. Vu	2022	47
Artificial Intelligence innovation of tourism businesses: From satisfied tourists to	Edward C.S. Ku Chun-Der Chen	2024	46
Measuring service quality based an customer emation. An explainable AI approach	Viting Guo; Yitin Li, De Liu, S. Xu	2023	36
AI concierge in the customer iournes” what is it and how can it add value to the customer?	Stephanie O, Liu, K. Vakeel, Nicholas A. Smirh. Roya Sadal Alavipour, C. Wei; Jochen	2024	34
Assessing an on site customer profiling and hyper, personalization system prototype based on a deep learning approach	Adrian Micu, Alexandru Capatina, Dragos Sebastian Cristea, Dan Manleanu, Angela-Eliza	2022	34
Affective Computing in Marketing Practical Implications and Research Opportunities Afforded by Emotionally Intelligent Mac-	Delphine Caruelle, Poja Shams Anders Gustafsson Amira Mouakher	2022	31
Collaboration with machines in B2B marketing, Overcoming managers’ aversion to AI CRM with explainability	Plotr-Gaczk, Grzegorz Leszezynski, Amira Mouakher	2023	23
Integrating Artificial Intelligence and Customer Experience	Veeraftow Gooljar; T. Issa, S. Hardin-Ramanan, Bilal Abu-Saith. Viltutian	2024	16

Fig. 4 Research on the impact of emotional AI (Top 25 Most Cited Studies).

Source Created by the author

Looking at Fig. 4, it is seen that there are studies revealing that emotional artificial intelligence (Emotional AI) has an impact on different research areas.

On a citation-based basis, Taherdoost and Madanchian [21], Han et al. [22], and Filieri et al. [23] rank highest. Han et al. [22] discussed how the emotional response of artificial intelligence systems in customer service shapes customer opinion, while Filieri [23] underlined the need to pay attention to emotions in service operations by focusing on the hybrid human–machine relationship. These studies reveal that Emotional AI is not just a technical tool but a strategic factor in its human-centric product and service-oriented design.

In the 2022–2024 period, research such as Chi and Vu [24], Ku and Chen [25], and Liu et al. [26] have addressed concrete examples of AI usage and applications in measuring customer feedback and loyalty, experience and service quality, and applications in the tourism sector. These studies stand out as they demonstrate the practical effects of Emotional AI in areas such as marketing, product and service management, as well as customer engagement. In particular, the study by Ku [25] explains the effects of emotional AI on customer loyalty in the tourism sector.

Although the number of citations is low [27] emphasize topics for improvement in the literature. These studies guide future academic research by drawing attention to issues such as the negative effects of artificial intelligence, ethical considerations, and multi-data approaches in sentiment analysis.

In this context, Fig. 4 is important in terms of both empirical and expanding the application areas of studies on emotional artificial intelligence in recent years. This trend suggests that Emotional AI will establish a multidisciplinary research area in the future.

Figure 5 shows the positions of the publications published in the Emotional AI and Business and Customer Services literature with the highest number of citations according to their time and citation density.

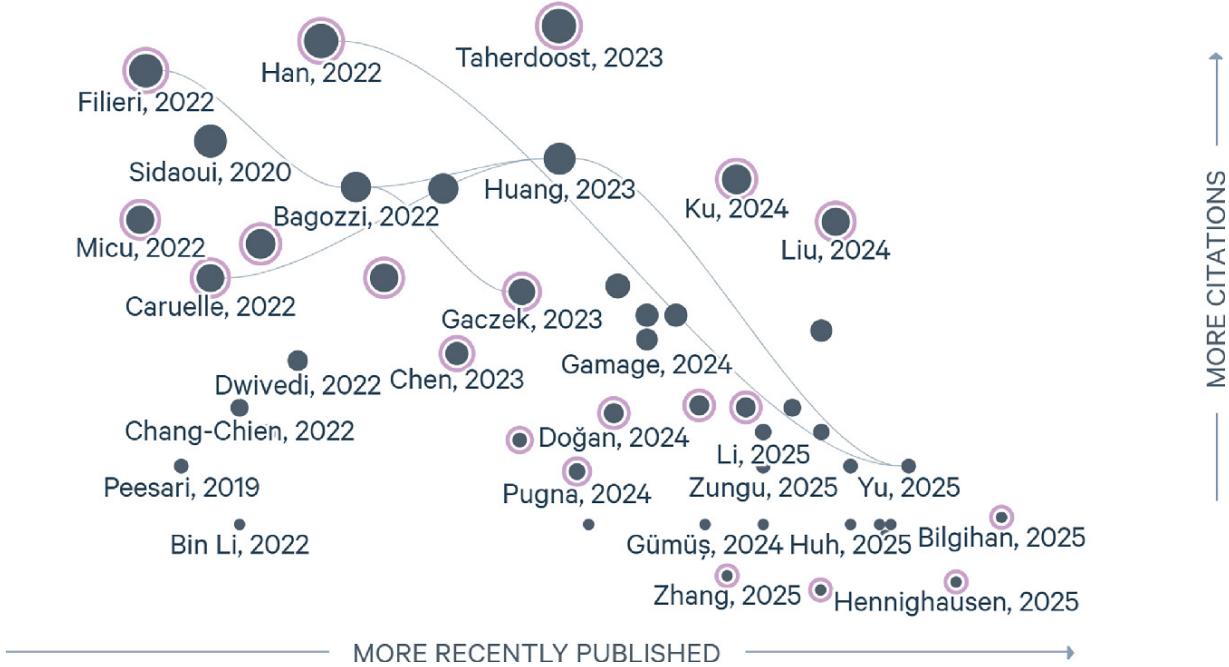


Fig. 5 Time and citation density of studies with the highest number of citations.

Source Created by the author

Looking at Fig. 4, studies published earlier than other periods, such as Filieri et al. [23], Sidaoui et al. [28] and Bagozzi et al. [29], have been a guide to empirical research. These studies have been guiding by shedding light on themes such as customer experience, consumer behavior, and product-service innovation in the context of emotional AI.

Studies such as Han et al. [22] and Taherdoost et al. [21] added value to the studies published before them, directing the remaining studies in empirical research to application areas, especially emphasizing themes such as human-artificial intelligence interaction and decision-making processes. The high number of citations of these studies indicates that the areas of influence in the literature are spreading rapidly.

Studies published in 2024 and 2025 [25, 26] received few citations due to the topicality of the research topics. In this context, it shows that research in the field has evolved from the early empirical framework to practice and multidisciplinary fields. With the transformation of technology, the focus of studies has become more human-centered, shifting to issues such as design, ethics and user experience. This shows that Emotional AI is not just about the technical dimension but has evolved into a field that covers many dimensions, from social sciences to the business world.

5 Result

This study reveals that Emotion AI technologies have significant impacts in different areas and are becoming increasingly important, especially in businesses and customer service areas. When we look at the research, it is seen that the applications are multifaceted. In the studies on human resources and the management of operational processes, it has been found that there are studies that take into account recruitment, employee loyalty, customer satisfaction and cultural issues and emphasize the concept of ethics. In the context of human resources, Emotion AI is increasingly being used in recruitment stages and employee performance tracking, ostensibly to enhance psychological safety and overall well-being [14]. Research on customer service shows that Emotion AI has a positive impact on customer satisfaction [30].

In this context, the findings reveal that Emotion AI technologies have become more than just a technical tool, but also a strategic factor influencing human-centered decision-making processes.

It is mostly used in human resources processes, from recruitment processes to performance evaluations, and supports critical issues such as choosing the right candidate, creating workplace loyalty, safety and ethics. In the field of customer service, the analysis of emotional reactions contributes to results such as customer experiences, creating a sense of empathy, and ensuring well-being. In this respect, Emotion AI stands out as a tool that not only evaluates the technical but also actively transforms the customer experience.

In addition, empirical research has included themes such as ethics, trust, data security and accountability in the studies. The fact that emotional intelligence varies according to cultural differences and the importance of multicultural approaches in the interface design and implementation of Emotion AI systems are also revealed.

As a result, Emotion AI will not only be a technological tool that provides a competitive advantage for businesses in the future and in future studies, but also a tool that aims to understand human behavior and create strategies accordingly.

6 Future Perspectives and Suggestions

In the light of the researches, it is obvious that in the context of the sustainability of Emotion AI in businesses, issues that are easy to interface, user-friendly, meet customer needs and give importance to customer experience should be taken into consideration. Kolomaznik et al. [31] state that socio-emotional competencies are important for humans and AI systems to create interrelationships.

Laying the groundwork for effective and healthy human-AI interaction depends on aspects such as engagement, empathy, customer experience, and making technology feel more usable [4]. Accountability, ethics, privacy, and security in this context are essential for the sustainability of Emotion AI.

In the development and implementation of these products and services, it is expected to turn into practice by taking into account the context of intercultural issues and to create social benefits beyond theory. In this context, Emotion AI is able to create interactive experiences for customers. From this point of view, failure to pay attention to these issues will prevent the progress of technical gains.

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Deep Learning Approaches and Technical Challenges in Facial Emotion Recognition (FER)

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Abstract

Nowadays, in every sector like mental health, physical health and education, communication plays a major role. The proper communication gives the accurate way of presentation for easy understanding. Proposed system experiments with facial emotion recognition that provides effective communication between system and people. The current system experimented on Cohn kanade (CK+) dataset for evaluation of all the seven facial emotion expressions which includes anger, contempt, disgust, fear, happiness, sadness, surprise conditions. Due to rapid growth in artificial intelligence tools, the regular interaction between people's communication is reduced day by day which leads to many mental health conditions which impacts on their performance. The usage of CK+ dataset includes variational emotions for effective facial emotion detection. The existing deep learning models proven that this dataset provides multiple variants of emotions for accurate analysis of facial emotions. The proposed system, Light—weight

fine-tuned Convolutional neural network (LW-fine-tuned CNN) model experimented with less number of layer for feature detection and produced an accuracy of 97.46 where as traditional feature extraction techniques includes local binary patterns and local directional patters and deep learning models (Alexnet, resnet and Mobile net) obtained an accuracy at the maximum of ninety five percentage. Along with accuracy, the precision, recall measures also limited up to 88% and 87%. To improve the performance, the proposed system fine-tuned the existing VGG-16 model and improved precision and recall from 7–10%. The proposed model addressed the technical challenges for effective emotion detection in the aspects of posing, lighting and expressions. The obtained results effectively identified the facial emotions.

Keywords Light-weight fine-tuned CNN – Local binary patterns – Local directional patterns – Alexnet – Resnet50 – Mobilenet

1 Introduction

In many of the cases of educationalists engaging more in system interactions, high engagement of those cases transformed to rapid growth in mental conditions which should be diagnosing with advanced social robots. In this, facial emotion detection plays a major role and the challenging conditions in FER datasets is class imbalance, where some emotions like Happy, Neutral dominate while others including Disgust, Fear are less represented. Real world conditions in deep learning and handcrafted feature-based FER approaches struggle to generalize.

However, existing FER methods face three challenges: Intra-class variation—The same emotion may look different across individuals. Uncontrolled conditions—Real-world datasets include occlusions, lighting variations, and partial faces. Feature irrelevance—Many facial regions (e.g., ears, hair) are not important for emotion recognition, yet traditional CNNs treat them equally. These limitations highlight the need for models that can attend to the most informative regions of the face while ignoring irrelevant cues. Inspired by advances in attention mechanisms, this work introduces an attentional CNN to tackle these issues.

2 Literature Review

2.1 Traditional Machine Learning (ML) Models

Though Machine Learning(ML) methods are applicable in various domains like health care, focus is made on Monitoring patient emotions, especially in mental health and Alzheimer's care, Security and Surveillance: Detecting suspicious or stressed behaviors, Automotive Industry: Driver drowsiness and distraction detection [1]. The major contributions are how SVM, RF, and ensemble models remain competitive against deep learning, highlight lightweight, interpretable FER systems suitable for real-world deployment and discuss integration with CNN feature extraction for enhanced accuracy.

The datasets used in this paper are FER2013: 35,887 images with labeled emotions, both CNN + SVM models surpass traditional ML-only methods, showing greater than 92% accuracy and ML approaches remain computationally lighter than deep neural networks, making effective results. Further processing with Extending ML-based FER models to large, diverse datasets such as AffectNet, Combining multimodal signals (speech, physiological signals) with facial expressions, developing explainable FER models for critical applications in healthcare and security and exploring lightweight, edge-friendly ML models for real-time deployment.

Paper [2] proposed the traditional ML approaches SVM and Random Forest classifiers showed high accuracy in static image-based FER, Ensemble learning improved robustness by combining multiple weak classifiers, Hybrid deep learning with traditional ML classifiers enhanced feature discrimination, Performance improvements ranged between 75–95% depending on the dataset and emotion class. The proposed framework for machine learning-based FER generally involves the following stages: Data Collection—Large-scale emotion datasets such as FER-2013, CK+, and AffectNet are used, Preprocessing—Includes face detection, alignment, normalization, and augmentation, Feature Extraction—Machine learning algorithms extract discriminative features such as Gabor filters, LBP, HOG, or deep features from CNN models, Classification—Algorithms such as Support Vector Machines are commonly applied for recognizing emotions.

The FER framework involves HOG-based feature extraction and classification using three ML models which includes the steps feature Extraction (HOG): Resized grayscale images (48×48), Computed gradient orientations, histogram bins (9 orientations, 8×8 cell size, 2×2 block

normalization), Generated robust descriptors capturing facial shape and texture. The proposed Machine Learning Models are Decision Tree (Gini Index) with simple, interpretable tree structure, Random Forest: Ensemble of trees with randomized feature selection and bootstrap sampling, SVM: Finds optimal hyperplane for separating emotion classes in high-dimensional space. SVM: Highest accuracy 58.93%. Best performance on happy (74.36% F1) and neutral (66.71% F1) [3].

2.2 Deep CNN Models

In the past, Facial Emotion Recognition (FER) systems used custom features such as contours [4]. These systems do not generalize well. They are not deep learning systems. They did not have access to feature extraction which classified elementary features. This resulted in dismal performance. This paper proposes EmoNeXt, which uses Cepstral Rooted Nonlinear Transfer (ConvNeXt) as the backbone for the deep architecture used in FER. The EmoNeXt produced decomposable state of the art performance on FER datasets with boost representation learning techniques, such as Spatial Transformer Networks (STN) and other features of the encoder architecture.

UNet segmentation: Extracts and isolates critical facial regions (eyes, mouth, forehead) to improve focus on emotional cues with steps: Input Image—UNet Segmentation—EfficientNetB4 Feature Extraction—Classifier. The obtained results are without UNet segmentation: EfficientNetB4 achieved 81.56% accuracy, outperforming CNNs, ResNet, and MobileNet. With UNet segmentation with happy, sad, fear, pain, anger, disgust emotions, EfficientNetB4: 91.27%, MobileNet: 89.94%, InceptionV3: 90.07%, Traditional ML models less than 81% [5].

The model in [6] consists of various layers, which are 5 convolutional layers with ReLU activation for effective feature extraction, this model trained on Datasets merged: JAFFE (213 images) + KDEF (4900 images) with augmentation steps Rotation, brightness adjustment, noise injection, and geometric transformations and Optimizer—SGD with LR = 0.01, batch size = 100, with epochs: Optimal at 300, on final training set: 14,200 images, test set: 1,580 images, Optimal CNN depth of 5 layers. The obtained Accuracy peaked at 78.1%, outperforming AlexNet (69.6%), VGG (68.7%), ResNet (71.2%), and GoogleNet (74.1%).

Deep learning models, especially CNNs, offer the potential for improved performance by automatically learning hierarchical facial representations. However, there are two main challenges. The first is capturing Emotion Constructs, which represent emotions in a structured and compact way [7]. In [8–12], the researchers focused on identifying compound emotion which is complex to handle the various conditions in emotions. Researchers have used datasets like the Multi-Emotion Facial Expression Dataset (iCV-MEFED), CFEE and RAFdb to train and test CNN models.

2.3 Hybrid Approaches

The study in [13] adds a new hybrid DCNN model with an extreme learning machine (ELM) to improve Facial Emotion Recognition Identification. Unlike the ELM or CNN only approaches, the hybrid model combines the strengths of ELM and DCNN by using DCNN for deep hierarchical feature extraction and ELM for fast classification, improving accuracy and real-time performance. The model features sub processes like stepwise linear discriminant analysis (SWLDA) and kernel filters.

The evaluation Methods in [14] includes subject-independent evaluation using K-fold cross-validation, Cross-dataset evaluation to test generalizability. Finally, the obtained results are conventional ML approaches that achieve high accuracy on small, controlled datasets (CK+ and JAFFE). Deep learning approaches consistently outperformed ML on large and diverse datasets (e.g., FER2013, AffectNet). CNN with transfer learning achieved state-of-the-art accuracy across benchmarks. Hybrid CNN-RNN models improved temporal emotion recognition (micro-expressions) and limitations remain in handling real-world variations, occlusions, and subtle expressions.

2.4 Diffusion Models

In [15], a strategy that combines **ResEmoteNet**, a CNN architecture with residual and squeeze-and-excitation blocks, with **synthetic data generated by diffusion models** (Stable Diffusion 2 and 3). By augmenting FER2013 and RAF-DB datasets, the proposed method significantly improves and achieves large performance gains over state-of-the-art models. FER systems often fail to generalize due to limited and imbalanced training datasets. Conventional augmentation (GAN-based) partially alleviates imbalance but

lacks realism. Recent **diffusion models** provide high-quality, diverse, controllable synthetic images, offering an effective solution. The goal is to use **diffusion-based augmentation** to improve ResEmoteNet's recognition capability across all emotion classes, especially underrepresented ones. In this proposed model,

2.5 Attention Mechanisms

In [16], the author focused on identifying complex emotions using various attention network models where many of the traditional methods are based on single attention networks. Attention Fusion Network (AFN) applies partition loss to penalize overlapping attention maps and fuses outputs from MAN for robust feature representation.

Facial expressions are a primary channel of non-verbal communication. Reliable FER is vital for healthcare, surveillance, driver safety, and human-computer interaction. However, conventional ML approaches require manual feature engineering and often fail under real-world conditions such as lighting variation, occlusion, and micro-expressions. Deep learning promises higher accuracy and generalization but demands large annotated datasets and high computational power. In [17], compared ML and DL approaches and provided guidance for future FER research.

The Deep-Emotion framework is an end-to-end attentional convolutional network (ACN) designed to selectively focus on salient facial regions. Feature Extraction Network: Four convolutional layers (3×3 kernels), each followed by ReLU activation and max-pooling, extract local features. Attention Mechanism (Spatial Transformer Network): A localization sub-network estimates affine transformations, warping the input image to focus on the most informative regions (eyes, mouth, eyebrows). The obtained results in [18] are: JAFFE: 92.8%.

3 Methodology

3.1 Dataset Description

Considered the following emotions from CK dataset [19, 20] for experimentation, with 981 images with a resolution of 48×48 pixels which includes train dataset with 80% (784 images) and test dataset with 20% (197 images) of 7 categories includes anger, contempt, disgust, fear, happiness, sadness, surprise conditions.

Preprocessing Methods: The steps include Face detection and alignment, Conversion to grayscale images, Image resizing to 48×48 pixels and Normalization of pixel values, for example, between 0 and 1.

Rationale for Choosing 48×48 Images: The 48×48 image size is frequently used in facial emotion recognition tasks. It provides a good balance between efficiency and capturing enough facial features for accurate emotion recognition. Many studies have adopted this size as a standard, which makes it easier to compare results across various models and methods.

3.2 Architecture Steps

1. Data Pre-processing done with extraction of the frames and resize the images to 48×48 pixels.
2. VGG16 architecture is considered a pre-trained VGG16 model, which consists of 16 layers, including convolutional, pooling, and fully connected layers.
3. We fine-tuned the VGG16 model by adding a flatten layer to the output of the VGG16 model to prepare it for fully connected layers.
4. Added dense layer with 256 units with relu activation
5. Added dense layer with 128 units with relu activation
6. Added dropout rate of 0.2 to reduce overfitting.

Finally defined the output layer with softmax activation for multi-class classification and trained the model using the adam optimizer and sparse categorical cross-entropy loss function.

3.3 Proposed System Architecture

See Fig. [1](#).

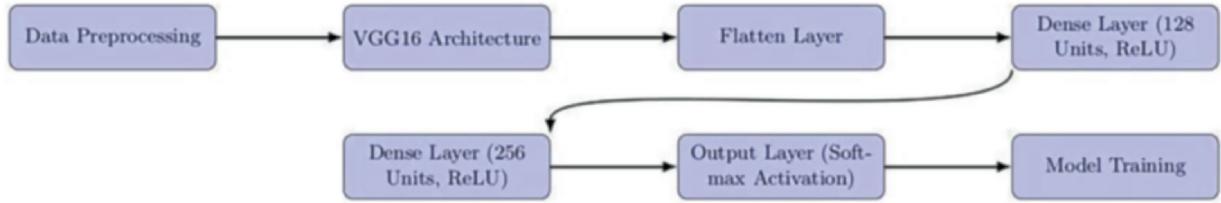


Fig. 1 Proposed system process flow diagram

4 Results Analysis

4.1 Training Accuracy

Proposed lightweight fine-tuned VGG16 model for FER trained with twenty epochs. The training accuracy is increased and loss is decreased when the iterations are incremental. On testing the model with the proposed Light—weight VGG16 model, obtained accuracy of 97.46% on CK+ dataset demonstrating the effectiveness in recognizing facial emotions. The validation technique used in this model with train—test split 80–20%. This accuracy shows that the proposed model is more effective than existing models.

Training accuracy and loss is depicted in the below diagram (Fig. 2).

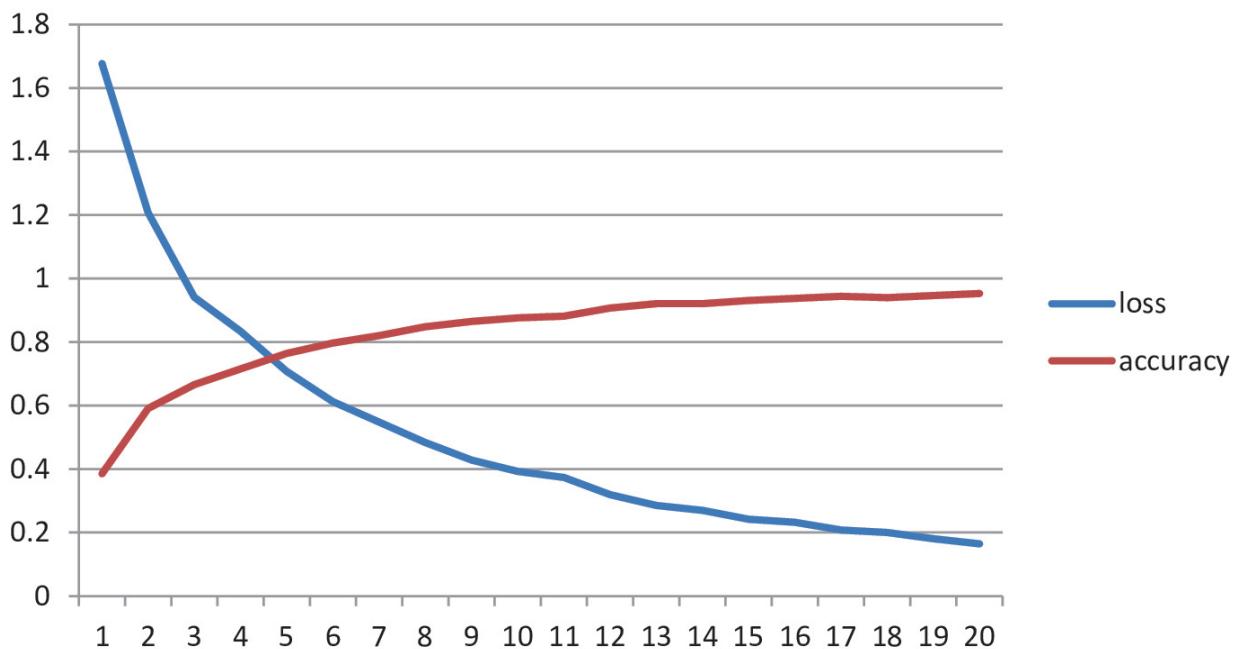


Fig. 2 Training accuracy chart

This comparison analysis evaluates the performance of proposed VGG16 against other deep learning models for facial emotion recognition. The models compared include: Proposed VGG16 implemented with 16 layers. The other models include Alex net with 5 convolutional layers and 3 fully connected layers. Another deep learning model residual learning-based CNN (ResNet50) with 50 layers and MobileNet CNN designed for mobile and embedded vision applications. The traditional models AlexNet, ResNet50, and MobileNet obtained an accuracy of 92.15%, 95.62% and 90.58% and precision, recall and f1-measure are shown in the Table 1.

Table 1 Accuracy, precision, recall and f1-measure results metrics

Model/Metric	Accuracy	Precision	Recall	F1-score
Alex Net	92.15	92.08	93.23	92.59
ResNet50	95.62	94.42	93.6	94.6
MobileNet	90.58	88.29	87.52	88.2
Proposed	96.46	95.63	97.25	96.43

The following section shows a comparison analysis diagram (Fig. 3).

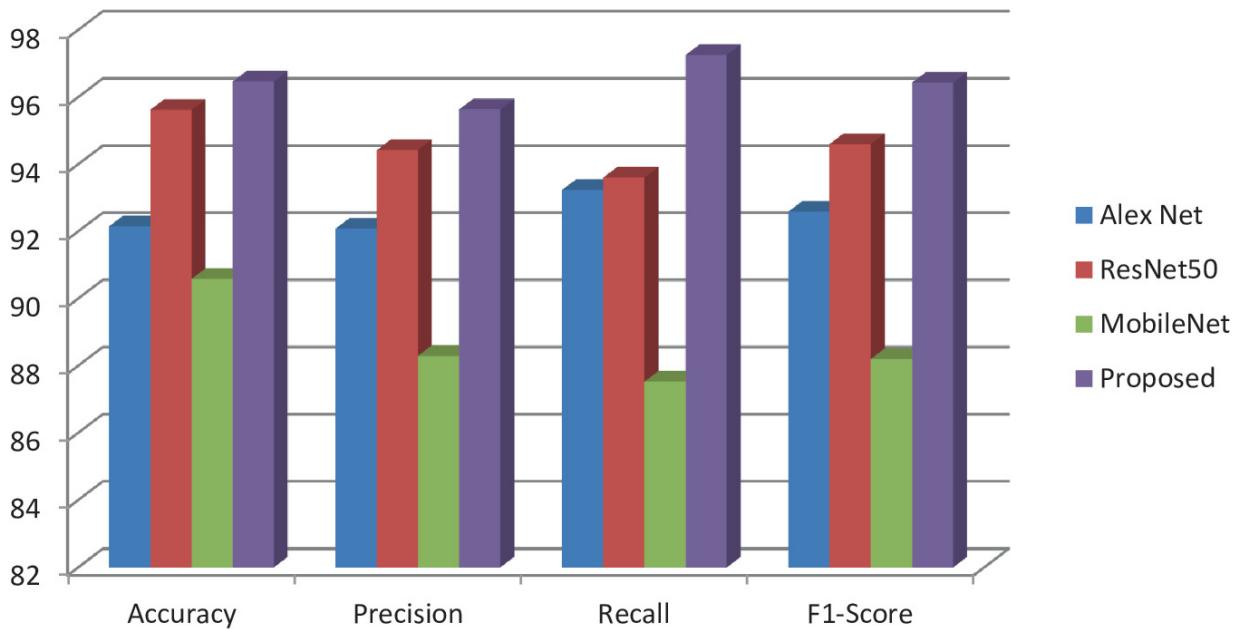


Fig. 3 Comparison analysis graph depicting metrics of proposed model, Alex ne, Resnet50 and Mobilenet

4.2 Confusion Matrix

A confusion matrix is a tabular representation utilized to assess the effectiveness of a classification model, including facial emotion recognition. It offers a comprehensive overview of accurate and inaccurate predictions in relation to the actual results.

True Positives (TP): The elements along the diagonal indicate the count of emotions that have been correctly classified (for instance, 27 for Anger).

False Positives (FP): The elements not on the diagonal signify the number of emotions that have been incorrectly classified (for example, 2 for anger that was predicted as contempt).

False Negatives (FN): The off-diagonal elements similarly denote the count of emotions that were not identified (Fig. 4).

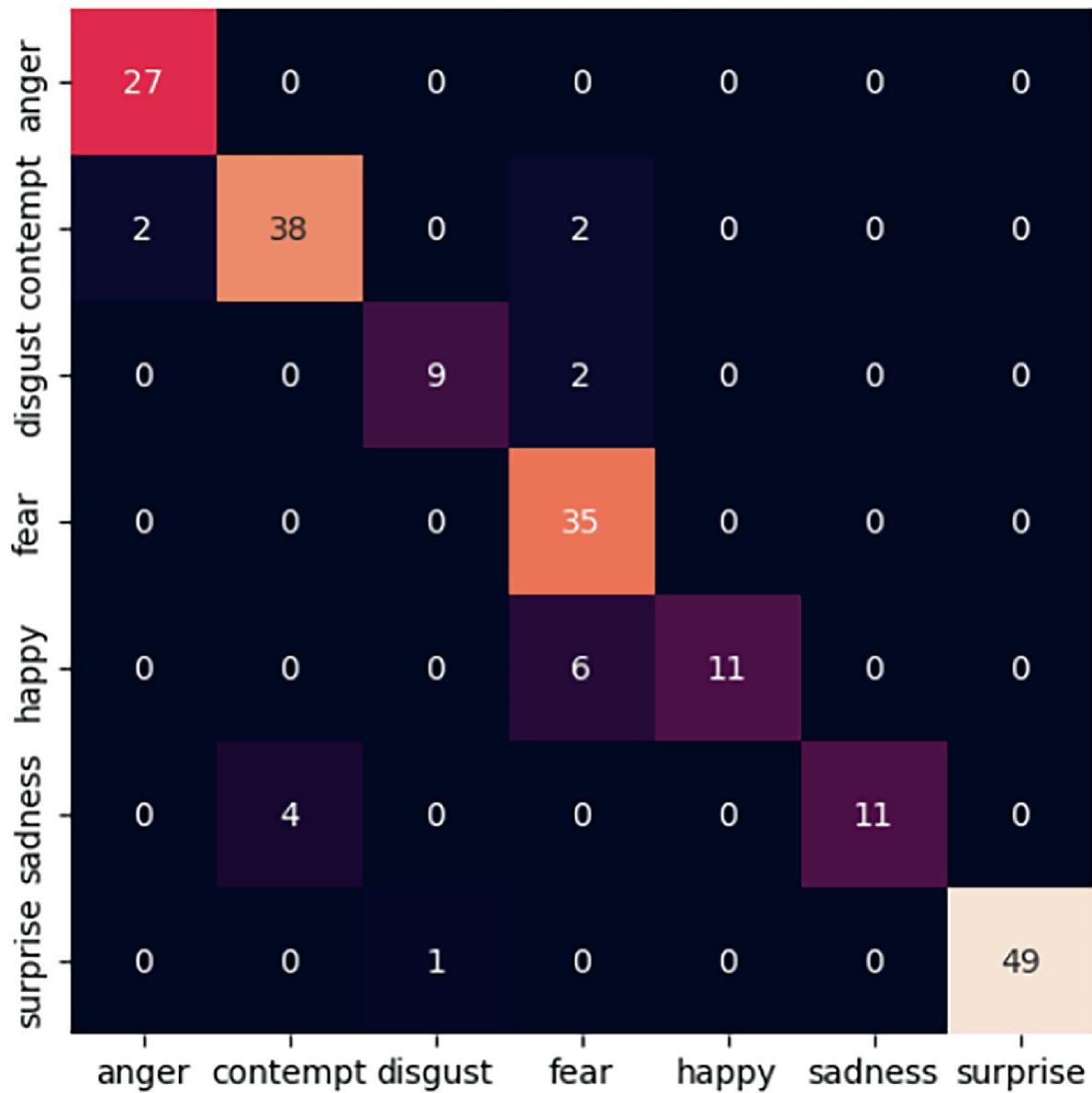


Fig. 4 Proposed model confusion matrix of facial emotion recognition

5 Technical Challenges and Future Directions

The major technical challenges include lighting, change detection and variant emotions. Along with the mentioned conditions the data imbalance where consideration of the number of images under each of the emotions leads to oversampling and under sampling conditions. Further by enhancing the emotion detection accuracy by including a combination of various emotion expressions with different types of data which is speech and other

physiological conditions. The current researchers are experimenting on multimodel emotion identification with challenging conditions.

6 Conclusion

The proposed research produced an accuracy of 97.46 whereas traditional feature extraction techniques including local binary patterns and local directional patterns are consuming high computational time with less number of images. By analysing the obtained results with other deep learning models including Alexnet, ResNet and Mobile net, it is proven that the Light-weight fine-tuned CNN model obtained effective results. Whereas the mentioned traditional methods obtained an accuracy at the maximum of ninety five percent and precision, recall measures also limited up to 88% and 87% on CK+ dataset. To improve the performance, the proposed system fine-tuned existing VGG-16 model and improved precision and recall from seven-ten percent. Furthermore, the proposed model is fine-tuned to fine compound emotions on CK+ dataset.

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Emotion Recognition and the Law: Bridging Technology and Human Rights

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Abstract

Emotions and facial expression recognition (FER) technologies are also some of the highest-demanding technologies aided by AI, which help to interpret human emotions through facial gestures for analyzing human behavior and processing them further for automated decision making. Though this technology has a widespread application in industries like healthcare, marketing, security, and education, it is, however, associated with some ethical and privacy concerns, as it works on personal biometric data and the chances of being influenced and monitored by others without seeking their individual consent. By gathering and analyzing the individual facial signs in the form of primary data, FER techniques frequently operate in opaque ways and thus raise some major ethical concerns, like consent, autonomy, transparency, and fairness. On the other hand, the universality and regional effectiveness of artificial models (used to recognize emotions) remained always questionable as they highly rely on assumptions without taking into account the cross-cultural aspects and human psychological facts under the fields of races, gender, and different age groups. This can further lead to diversified inequalities, communal disagreement, and

adverse social implications. Therefore, it is high time to evaluate the existing FER technologies with the integration of AI through the dual lenses of human ethics and law. Hence, this chapter tries to give some glimpse of the lacunas in the existing systems, and thus a comprehensive regulatory framework is to be proposed by considering the current legislation both at the regional and international levels in order to maintain the human values and individual dignity.

Keywords Facial Expression Recognition (FER) – Data privacy – AI technologies – Human rights – Legal frameworks

1 Introduction

Facial expression recognition (FER) is nothing but a fundamental aspect of non-verbal social communication techniques, which uses the facial cues to exchange thoughts or emotional states between humans and machines. As the FER systems try to decode different human-oriented non-verbal emotions such as anger, happiness, surprise, and sadness, at the present scenario these systems are becoming the significant role players in the fields of education, security, and health-care to enable a common platform where the machines can smoothly interact with the humans and vice-versa [1, 2]. Being a key technology under behavioral science, FER allows machines to interpret human emotions to improve mental health conditions and to diagnose rare neurological and debilitating disorders like Parkinson's disease and bipolar disorder etc. [3]. A gradual progress of the FER system requires continuous updation to integrate nuanced human interactions and to deliver processed personalized responses by extending the scopes both for academic research and practical implementations [4].

With the rapid advancement of technology, artificial intelligence (AI) is transforming many sectors, including human behavior analysis by acquiring more detailed and scalable insights on how people feel, think, and act etc., and processing the same for the detection of emotional states and prediction of behavioral consequences [5]. Introduction of AI also enables a controlled approach towards personalized learning, behavioral changes, and mental health issues. By monitoring and analyzing the real-time data, AI AI-aided system can deliver just-in-time adaptive solutions for addiction type treatment and health behavior changes [6]. Certain new characteristics

related to sociology, political science, and psychology can also be unveiled by processing numerous already existing behavioral patterns through AI-enabled systems [7]. So, it can be stated that the analysis of human behaviors is gradually modernizing with scalable, personalized, and precise insights by incorporating AI into different systems, but the ethical and societal consequences of this modernization need to be addressed properly.

Based on the above fundamentals, the present chapter aims to cover the available technologies for FER and possible extensions of those technologies from the viewpoint of the ethical and societal implications. This chapter also tries to explore the challenges and consequences related to privacy, surveillance, consent, and bias arising due to the integration of AI into FER techniques. On a final note, it can be mentioned here that this chapter will act as a rational combination of ethics, technology, law, and human rights by allowing an interdisciplinary approach to the field of human behavioral analysis.

Broadly, the objectives of the present chapter can be listed as:

- To get familiar with the available technologies for FER and to explore the associated limitations.
 - To look into how to mold the legal frameworks so that the FER technologies can be deployed without affecting the fundamental rights to freedom of expression and rights to privacy.
 - To regenerate the awareness among the public, policy makers, legal professionals, and technocrats so that the latest AI-enabled FER technologies can be implemented smoothly.
-

2 Fundamentals of Emotion Recognition and FER in AI

As FER can be treated as a multi-disciplinary approach to comprehend human emotional states from facial signals by integrating computer vision, psychology, and AI, it is necessary to understand the core definitions and key concepts related to FER.

- Emotion Recognition (ER): This uses different physiological signals, forms of speech, and facial expressions to imitate human emotional intelligence using certain machines [8, 9].

- FER: Being a subset of ER, FER emphasizes only facial muscle activities to analyze and identify the emotional states. Commonly, this deals with six to seven emotions (like fear, anger, happiness, disgust, sadness, neutral, and surprise) based upon the received expression patterns [8, 9].

The key concepts supporting the FER technique can be listed as per below:

- Basic Emotion Theory: The fundamental concept of FER can be directly linked with Ekman's theory of universal emotions, which postulates that certain emotions are biologically hardwired and universally expressed through similar facial patterns [10].
- Feature Extraction: By applying methods like Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and Principal Component Analysis (PCA), FER examines facial textures, geometries, and landmarks to bring out the significant features [11].
- Classification Models: Based on the extracted features, the emotions are classified through some of the machine learning and deep learning algorithms, including Convolutional Neural Networks (CNNs), k-Nearest Neighbors (k-NN), and Support Vector Machines (SVMs) [12].
- Emotion Distribution Recognition: Commonly, expressions may carry an amalgamation of multiple emotions, which can be presented through Emotion Distribution Learning (EDL) technique by applying probability distribution methods [13].

To discern emotions, different psychological theories are technologically integrated, so that ER and FER can be performed precisely by some machines. The advancement of technology requires the advent of AI in the existing fields so that the application potential of such techniques can further be extended to various arenas such as education, security, and health care. Besides earlier concepts, there also exist some AI-based techniques that can strengthen the technological architecture of emotion and facial expression recognition processes. Some of these technologies are:

- CNNs: These can be referred to as the backbone of modern FER systems, which are capable of recognizing emotion patterns by extracting special characteristics from images. Further, classify them in the forms of anger, sadness, and happiness [14].
- Multimodal Emotion Recognition: To address the shortcomings of single modality systems, AI-enabled systems now simultaneously operate on the

combination of a wide range of data, including speech signals, facial expressions, and physiological data (such as pattern of heart rate and ECG), which further enhances the detection accuracy and context-awareness [15].

- Real-time Face Detection and Tracking: To detect, track, and analyze the dynamic facial emotions in real time, algorithms like YOLOv10 can be incorporated in video conferencing and education sectors [16].
- Explainable AI (XAI): At present, FER systems are integrated with the latest tools (like Grad-CAM), which are capable of emphasizing the facial features that extremely influence the prediction process [16].
- Emotion AI in Human–Robot Interaction: In the field of robotics, FER systems are aided with AI and IoT to smooth the functions of educational companions and emotion-aware service robots [17].

In addition to deep learning, multimodal processing, and computer vision, modern FER systems are to be integrated with AI to identify and respond to human emotions accurately.

3 Threats and Risks Associated with AI-Enabled FER Systems

Industries like marketing, education, health care, and security are ready to adopt the rapid transformations to integrate AI with FER systems. So that human emotions can easily be interpreted by machines. Whereas, the associated threats concerning ethics, privacy, security, and bias need to be addressed with effective resolutions. Below-mentioned are some of the major threats that can never be ignored:

- Limitations of Universality Assumptions: FER systems are developed on the assumptions of universality, backed by Paul Ekman's theory of six basic emotions, i.e., anger, surprise, happiness, fear, disgust, and sadness, which are universally recognised across all humans. Though this framework assists in training AI models, but lacks to effectively address groups of diverse races, societies, and cultures. Considering the aspects of cultural differences, it has been seen that emotional expressions vary across cultures as compared to individual ones. For instance, East Asian people will quash negative emotions to maintain group harmony, but Western populations focus more on individual emotional expressions.

Thus, FER systems trained on Western datasets fail to recognise emotions among non-Western populations. In line with this, articles highlighted the limitations of universality assumptions for the effective working of AI-based FER models are summarized in Table 1.

Table 1 Limitations of universality assumptions in FER models

Limitation	Description	Example	References
Contextual dependence	Without prioritizing linguistic and contextual clues, only facial expressions may not always convey accurate emotions	Sometimes a smile can be a symbol of satisfaction, but in other cases it can also portray discomfort	Barrett [18]
Cultural variation	Cultural variances in manifestation and emotion identification raise doubts about the notion of universal expressions	East Asian people will quash negative emotions to maintain group harmony, but Western populations focus more on individual emotional expressions	Barrett et al. [19]
Racial and demographic bias	Training datasets with over-presentation of Western, lighter-skinned faces may lead to reduced accuracy for minority groups	FER models are prone to misclassifying emotions in older adults, dark-skinned people, and women	Kaur and Kumar [4]
Morphological differences	The recognition accuracy also gets affected by variations in facial structures	Differences in eyelid shape or facial musculature alter how emotions are visually expressed	Kaur and Kumar [4]
Ethical risks	Emotion misinterpretation can result in bias, loss of autonomy, and discrimination	During legal trials or airport security screening, errors in judgment may occur due to misclassification of ‘fear’ or ‘anger’	Peng et al. [20]

The over-simplification of context-mediated, complex, and culturally situated features of human emotions is carried in AI-based FER models by adopting the universality assumptions. If the upcoming FER systems fail to address the above-mentioned limitations, then ethical accountability and accuracy of these models will remain doubtful, with the chances of systematic misrepresentation and bias.

- Privacy Infraction and Unofficial Surveillance: One of the most serious concerns of AI-enabled FER systems is related to their potential application for mass surveillance and infringement of individual privacy.

The arising of ethical and legal concerns with these systems can be attributed to monitoring individuals without their proper consent and collecting sensitive emotional data from public places or online platforms. These systems are also capable of converting human emotions into some lax data points, which can further be used for profiling. As any structured regulatory norms for these systems are missing, different firms and government bodies are unable to fix clear boundaries to enact against the violation of emotional freedom and the individual right to privacy [20].

- Algorithmic Bias and Discrimination: Due to a lack of a diversified training dataset, FER systems are inherently associated with biases. Often, the analysis on this dataset can result in skewed outcomes as there exists a chance of over-presentation of characteristics on the basis of age or ethnicity, or gender. As an outcome, the individual emotions related to underrepresented groups may be inaccurately classified or misinterpreted by the FER models. This collection of biases produces outcomes that are discriminatory in nature and affects the recruitment process and law enforcement, where misinterpretation needs to be avoided [4].
- Antagonistic Attacks and System Manipulation: AI-based FER systems are prone to antagonistic attacks, as a result of which the whole system can be deceived by anonymous agents through finely altering the input dataset (like facial features or images). Due to these manipulations, FER models often misclassify the intended identities or emotions, raising serious concerns in severely sensitive applications like crime detection or border control. For example, a violator could apply makeup or other accessories to spoof facial characteristics and evade detection [21].
- Deep-fakes and Identity Spoofing: The quick outspreading of synthetic social media or deep-fakes is another fatal threat associated with AI-based FER systems, as these systems are susceptible to manipulation using AI-generated fake facial videos, in which the real individuals are seen to express false emotions. The outcomes of these may lead to falsification of information, reputational damage, or identity theft. So the manipulated deep-fake contents might be interpreted as authentic emotional expressions due to the lack of robust anti-spoofing mechanisms in the existing FER systems [22].
- Psychological and Social Impacts: The FER systems are also associated with the rising concerns related to the psychological impacts which are

caused due to the constant monitoring of individuals by the systems, and this continual surveillance may result in undesirable stresses, altered behavior, and reduced genuineness in the communication process. These can also lead to the augmentation of existing inequalities in society by affecting the marginal communities in a severe way [4].

- Ethical and Governing Gaps: Regardless of their quick deployment, FER systems may outperform by ignoring the ethical and legal guidelines. Lack of transparent and globally accepted governing laws with respect to emotional data collection, usage, and individual consent, however, raises a serious concern of misuse of FER systems by the authorities or corporations to manipulate the actual data [20].

Apart from the above-mentioned threats, AI-based FER systems witness some critical challenges related to societal, psychological, and ethical aspects for the smooth execution of this advanced technology, which are presented in Fig. 1.

Challenges in Facial Emotion Recognition

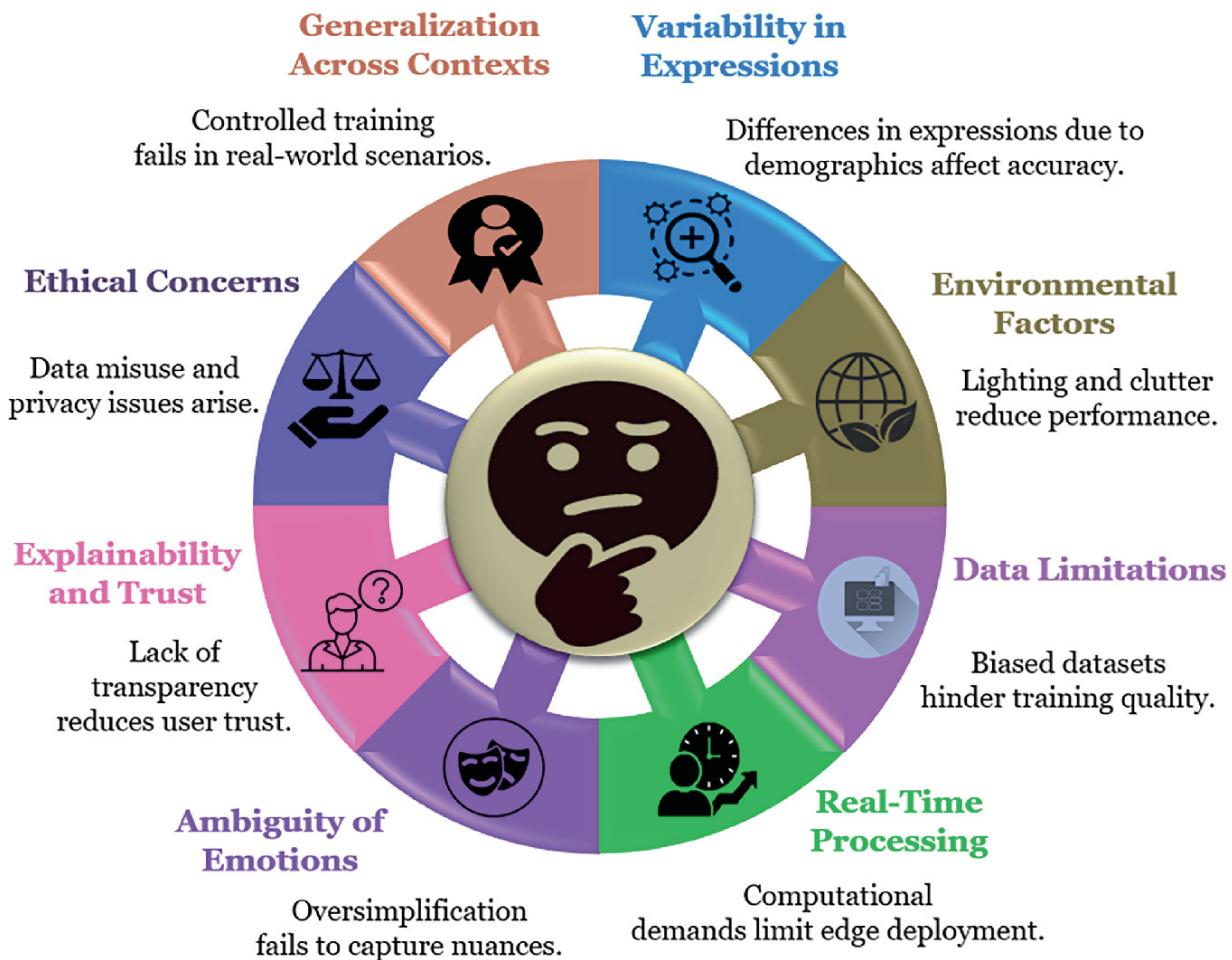


Fig. 1 Common challenges witnessed by AI-based FER systems

4 Key Challenges

When a new technology enters to the field of execution, it is evident that it may face a variety of challenges along its path. But each of the challenges requires much attention for the smooth execution of AI-based FER models. Some major challenges are hence discussed as per the following.

4.1 Ethical Aspects Related to AI

In the era of globalism, AI is the most sought-after innovations that increasingly impact decision-making, interactions, transactions, and ethical

considerations about human life. Apart from being a boon for human civilization, it poses many risks, particularly concerning ethical theories and law. The exponential rise of AI has coerced humanity to reconsider and reimagine its traditional philosophical frameworks. All the traditional jurisprudential theories, like utilitarianism, deontology, and virtue ethics, that were coined by great philosophers, have been limited by the consistent use of AI. Furthermore, it has started transcending human capabilities [23].

In layman's terms, "ethics" is something that can determine an action to be good or bad. Likewise, ethical theories are envisaged with the obligation of concluding what makes an action good or bad. There are two widely known theories of deontology and consequentialism of the eighteenth-century Enlightenment period that are the answer to this discord [24].

There are multiple concerns relating to consent, transparency, and fairness that the AI-based ER poses. For instance, AI-based ER needs to facilitate real-time user control *in tandem* with transparent data-governance frameworks. Similarly, consent management requires open-communication frameworks to allow individuals to control their emotional data access. Also, algorithmic bias creates a lot of problems in ER research. This bias arises when model accuracy and predictions vary inequitably across demographic, racial, or cross-cultural groups [25]. Some of the vital aspects of ethical concerns can be understood from Fig. 2.

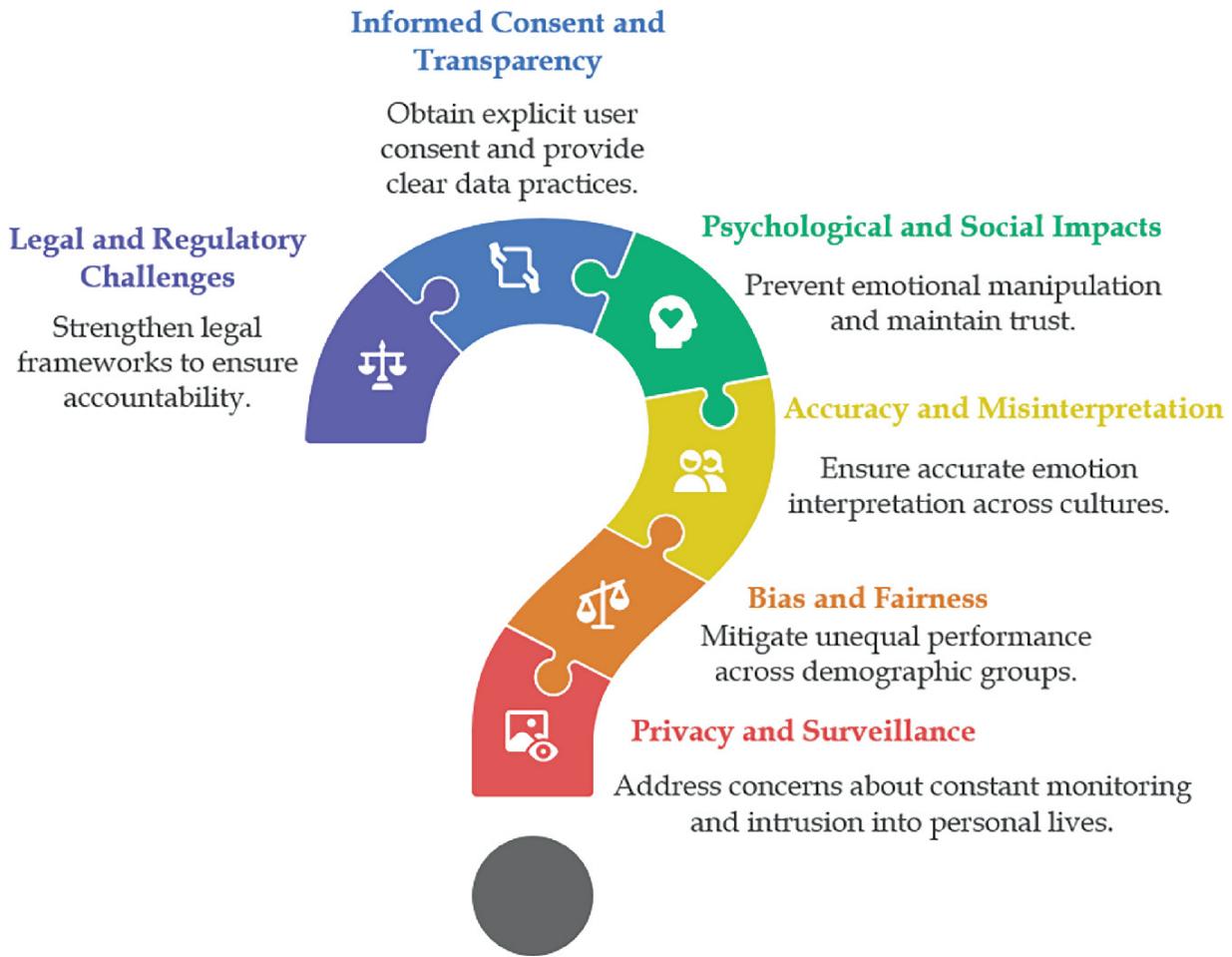


Fig. 2 Some major aspects of ethical concerns related to AI-based FER models

Therefore, different ethical theories need to be understood with respect to AI.

- Utilitarianism: Utilitarianism, propounded by Jeremy Bentham and later by John Stuart Mill, advocates the theory of maximizing overall welfare and achieving “greatest good for the greatest number” [26]. In contemporary times, AI can be used to enhance the welfare policies of governments by incorporating it into the healthcare sector. AI can analyse and store data of the greatest number of patients and smoothly facilitate their treatment process, thus, making the lives of doctors a bit easier. Similarly, AI is known to make economically feasible decisions. So, deploying AI in the criminal justice system will be beneficial in contemplating potential benefits against risks. Although AI ethics may have an enormous impact on the “greatest numbers,” it still poses significant obstacles in the way of implementation. As minority rights

will be infringed upon while achieving greater efficiency for the majority [24].

- Deontology: The most prominent advocate of deontology is Immanuel Kant. It emphasizes the need to adhere to moral rules and obligations regardless of the further consequences. Deontology asserts to protect individual rights regardless of the outcomes. In the spectrum of AI, it is challenging to abide by the theory. It endows the developer with a very daunting task to safeguard the privacy rights of the users. Apparently, there are many chances that it will resort to discriminatory practices. Also, there is another perennial strife between the obligations of the developer to safeguard the privacy of the user *vis-à-vis* ensuring public safety in scenarios where technology for surveillance is used [27].
- Virtue Ethics: The last ethical theory for deliberation was enunciated by Aristotle. Virtue ethics focuses on virtuous traits that help a human determine what kind of person he is. It encapsulates high morals, grit, audacity, and empathy that a human holds. AI is oblivious about such emotions and attributes, and it is quite impossible to weave these into the technology [28].

Thus, these ethics are crucial for the development of the human race, but infeasible for AI to attain them.

4.2 Right to Privacy and AI-Bias

Emotion AI is an intrusive tool used for several purposes, such as security and verification of a person's identity, or at times to study customer behaviour. In more exploratory use, FER can be used to obtain demographic details of a human being, like age, gender, sexuality, and much more. In this context, the major question is how these datasets will deduce such information [29]. For example, ChatGPT currently introduced Ghibli, used to convert photos into anime portraits. Apart from doing so, Ghibli recognized and stored the emotional undertone of the picture. Some major aspects of the right to privacy and AI-bias and their consequences can be presented through Fig. 3.

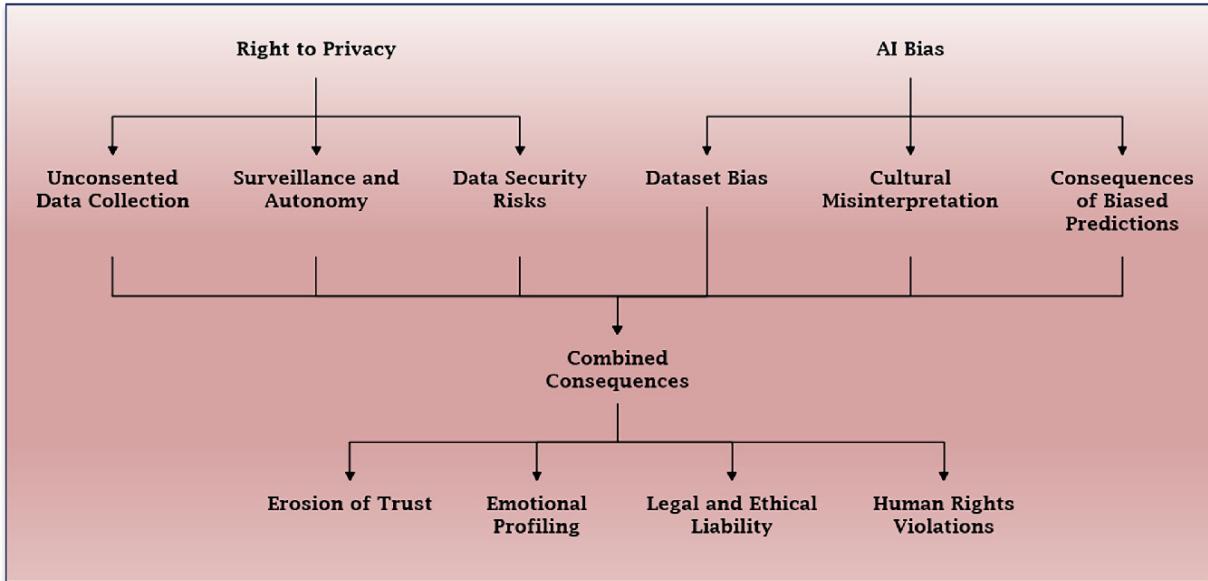


Fig. 3 Right to privacy and AI-bias and their consequences for FER models

Similarly, these days, police are using FER to discern whether a person in the crowd is going to commit a crime or not. Likewise, governments are using the technology to track the movement of people on their radar. Although these FER may be spine-chilling, but can be used to mitigate terrorism and all potential threats to national security [30]. Also, there is a fine line *in tandem* between FER's security protections and privacy violations.

- Global Privacy concerns: Article 12 of the Universal Declaration of Human Rights (UDHR) and Article 17 of the International Covenant on Civil and Political Rights (ICCPR) envisage 'right to privacy' as a fundamental human right. So, any technology that accesses a human's feelings without their voluntary consent shall infringe their fundamental human right. Other than for security purposes, listening to or recording telephonic or electronic conversations of private citizens is allowed in some states. Whereas, certain states require the prior informed consent of both parties [31]. Now the bone of contention is whether capturing feelings and thoughts would fit under this legal framework. Another critical concern is who are the parties when AI captures feelings and thoughts?

In unpacking these complexities surrounding security protections and privacy violations, let us unravel the "self-regulation" phenomenon. In New Zealand and Australia, there is a legal vacuum concerning the use of FER

technology by police and security organisations, as there is no legislation to prohibit or empower it. The decision to employ FER is solely made by these agencies internally without the consent of the general public. Also, there is a mere possibility for the police to take arbitrary and evasive decisions without any parameters for deployment of FERs [32].

Recently, in *R (Bridges) v. the Chief Constable of South Wales Police* (2020), the South Wales Police used an automated facial recognition system (AFR) to scan the faces of individuals at public places without their informed consent. The Court in this case held that the AFR was not “in accordance with the law” under Article 8 of the European Convention on Human Rights and the UK Data Protection Act 2018. The Court further stated that the FER created gender and racial disparities and gave wide powers to the Police to act on its behest [33].

- Disparities surrounding race and gender: When it comes to identifying the colour of skin colour of different people, FRE’s work is unsatisfactory. Consequently, FRE is incapable of retaining higher racial diversity in its own dataset. Also, FER has a substantial gender bias in its algorithm data, failing to identify fluidity in gender. It only identifies male or female; the queer community is erroneously labelled. There is a constant stereotypical representation in the algorithm of any individual who wears a dress and makeup as a woman [30]. Also, empirical survey-based research demonstrates that FER is dogmatic against minorities. As it is inexact and vague for the faces of women and people of colour [34].

Companies heavily rely on datasets of facial images to train their algorithms. Sometimes this is carried out without the voluntary consent of the concerned individual [35]. These images can be acquired from different sources, like social media, dating sites, CCTV cameras, and much more [36]. The algorithms deployed have proprietary sensitivity, thus, abstained from public disclosure [37]. Furthermore, when biometric data is stolen, it can be reset and retrieved, but the transgression of FER cannot be reset [30]. Therefore, FER is the most volatile form of technology that can potentially violate the privacy rights of many. Although privacy is a basic principle of international human rights law but it is not defined in any international instrument. Notwithstanding that ICCPR stands as an authority that guarantees ‘right to privacy’ but it cannot be held as a firewall for

current technological advancements. Any kind of breach by Emotion AI and FER algorithms can only be catered to by new-age novel laws.

4.3 Psychological and Social Impacts

Face is an inalienable part of human day-to-day lives. A ‘facial expression’ can determine the mental and emotional state of a human being. Tech giants are making enormous financial and material investments to read emotions and detect and understand their facial expressions. For example, Microsoft has developed an Emotion Application Programming Interface (API) that detects different emotions of human beings like happiness, anger, disgust, grief, and much more [19]. Similarly, facial expressions are used to read the emotions and mental state of patients having psychiatric disorders like autism. This facial configuration is indispensable in such diagnosis and treatment [38]. Likewise, United States Supreme Court Justice Anthony Kennedy quoted that “*reading the emotions of the defendant is knowing the heart and mind of the offender*” [39].

It is well established that exposure to FER may lead to a violation of individual privacy. It is not a concern for people who do not express much and remain neutral, but the ones who vividly express their emotions are subjected to technological scrutiny and surveillance. However, FER is an appropriate platform for teaching, but it can prove to be a misguided channel to share secrets and vulnerabilities. On the other hand, FERs are incompetent to demonstrate empathy and compassion when humans share their problems. Then, after, humans become disheartened and get swayed away when they get such unnatural empathetic responses [40]. This erodes human emotions and makes them go after something that is abstract and transient. If the current state persists with the sporadic expansion of Emotion AI and FER, then it will exacerbate systemic discrimination and stigma in society and will pose adverse effects on society [41]. Therefore, technology should serve us, not rule us. Thus, a brief presentation of this can be displayed through Fig. 4

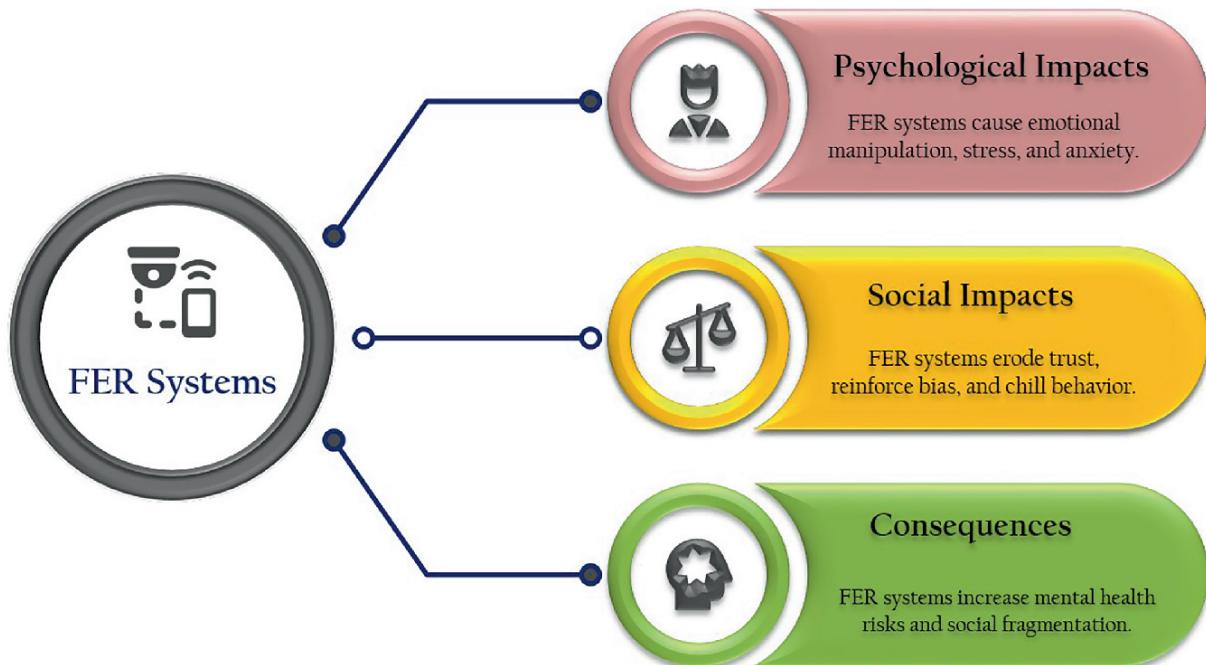


Fig. 4 The psychological and social impacts of FER systems and their consequences

5 Regulatory Frameworks Related to FER Techniques

The states are entrusted with the utmost duty of safeguarding the privacy and dignity of their subjects under international law. Transcending beyond normative legal frameworks of privacy and data protection, these FER technologies are an imminent danger to the ‘freedom of our inner existence’ as held by the European Court of Human Rights (ECHR) [42]. When we ruminate on the legal and ethical implications of ‘emotional data,’ there comes a dire need to define “emotions” and then “emotional data” in a legal context [43]. Before discussing nascent ongoing deliberations on Emotional AI and FER, let us first analyse the existing framework.

5.1 Integrated Regime of GDPR and ECHR

The European Union’s (EU’s) General Data Protection Regulation (GDPR) came into effect in the year 2018. GDPR mandates a clear and lawful basis for personal data processing. The biometric data found under Article 4 (14) of the GDPR is procured via conforming to special techniques relating to unique physical, physiological, or behavioural attributes of a natural person,

including facial images or dactyloscopic data. Although the traits of a human face are unique, it can still be considered as a kind of biometric data. Due to the biometric quality, if the facial detection is already personal data, then it shall come under the purview of sensitive data under Article 9(1) of the GDPR. Under the GDPR framework, special consent needs to be obtained when such sensitive data is used [43]. Further, it directs stringent measures to be followed when a special category of personal data is processed [44].

With the rapid advancements of technology, GDPR is unable to keep pace, including its application to new technologies like FER. In the EU context, laws relating to privacy exert greater influence than data protection laws (GDPR). Therefore, the European Convention on Human Rights (ECHR) is more systemic in enforcing individual rights regarding FER. In regard to addressing the demand for ethical responsibility of FER, both GDPR and ECHR, and the domestic Human Rights framework within EU states have to be invoked in the adjudication process [44].

5.2 Emerging Trends in FER Technologies

FER is a complex technological dataset that calls for robust laws to be enacted to protect individual privacy and freedom of speech and expression. For regulating AI, preliminary work has started at the international level. In furtherance of the same, the Organisation for Economic Co-operation and Development (OECD) principles on AI were adopted in May 2019. It states that overall deployment of AI, including FER, should be done in consonance with the ‘rule of law.’ The G-20 states have also shown faith in these principles. A comprehensive and enforceable rule concerning FER is crucial in the legal arena [45].

5.3 Global Divide in AI Regulation

In the global scenario, there is a divide in AI regulation. There is a need for a unified, coherent, and comprehensive framework for its regulation. Different states follow different structures; the UK is pioneering in the data protection laws, whereas the US has a more decentralized approach, where individual states have their own legal framework for addressing AI bias. For instance, California has its own statute on ‘Privacy Rights.’ Similarly, EU states, Canada, and Brazil have a ‘horizontal’ framework of addressing common issues relating to AI. Despite this split in the contemporary world,

we need a uniform and robust international regime on AI regulation concerning FER technologies [46].

6 Recommendations and Future Scopes for AI-Based FER

To smoothly implement the AI-based FER technology, the critical challenges related to legal conflicts, psychological inconsistencies, and ethical and privacy discriminations must be thoroughly addressed. To incorporate the ethical theories with the practical governance system, the following recommendations may be helpful:

- AI systems should ensure the embedding of ethical principles from the foundation itself by balancing the deontological commitments with the utilitarian benefits. Care should also be taken so that the designated systems can serve for public welfare without affecting individual rights, especially for minority and vulnerable communities.
- An identical international regulatory framework is highly essential to bridge the fragmented global policies in AI governance. This should cover the aspects of the Universal Declaration of Human Rights with the expanded definitions of ECHR and GDPR explicitly for emotional data by ensuring legal protection to inner expression and individual dignity.
- Collection of facial and emotional data must be facilitated with informed and opt-in consent from the individuals. In accordance with articles 12 (UDHR) and 17 (ICCPR), governments must prioritize to legally differentiate the concepts of security-based surveillance and privacy-invasive emotional monitoring.
- To avoid common discriminations in culture, gender, race, and communities, developers should look for algorithmic fairness protocols to enable diversity in training datasets and transparency in model formations.
- Before deploying FER models in public domains as workplaces, healthcare centers, or schools, the users need to be educated regarding the model execution and how their emotions are being interpreted in the models, so that mental wellness can be ensured.

Along with the above recommendations, researchers and policy makers may also look into the future scopes of AI-based FER models so that the

systems can be user-friendly and simultaneously protect one's right to privacy without affecting the ethical concerns. Figure 5 depicts the future scopes or directions to expand the FER technology further.

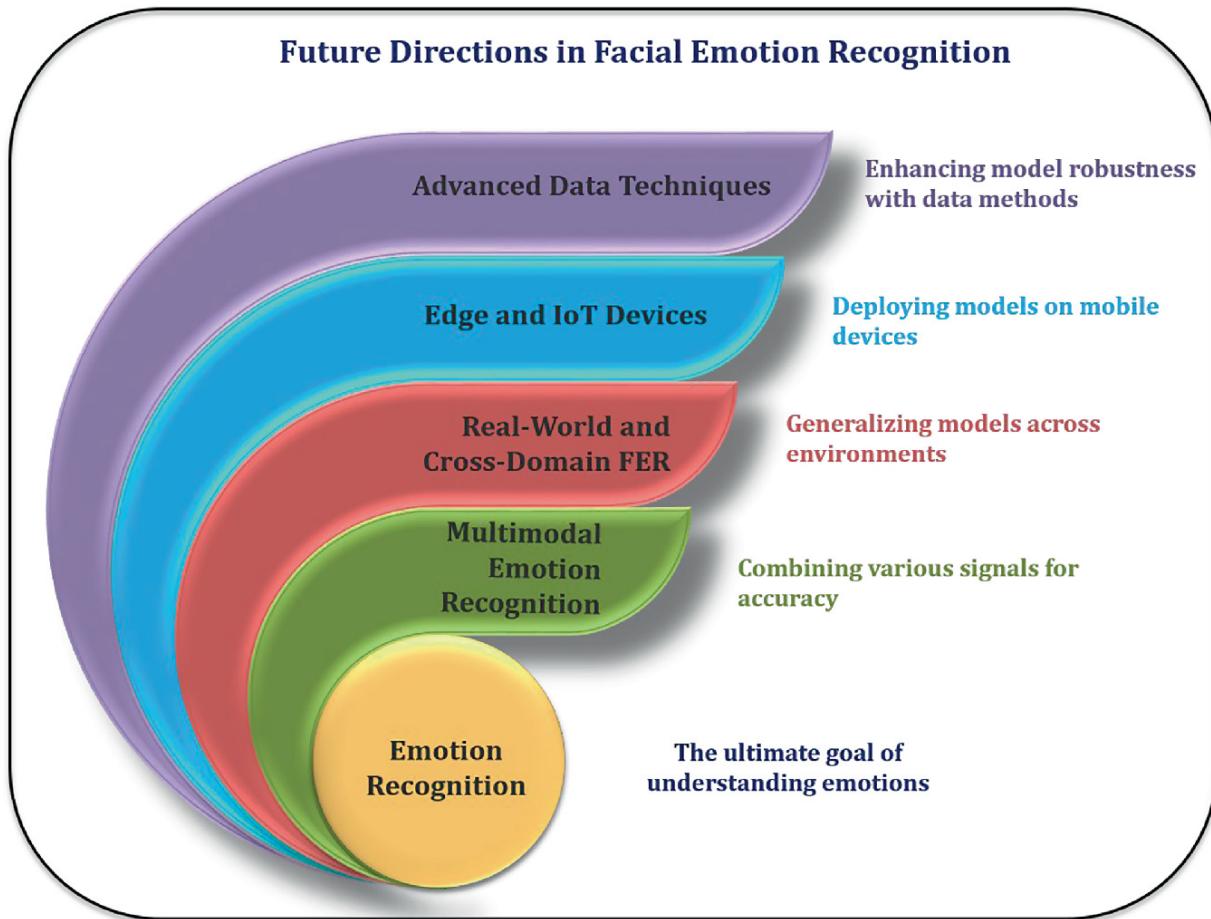


Fig. 5 Future research directions of AI-based FER systems

7 Key Takeaway Points from the Total Discussion

Through this chapter, an attempt is made to represent the current scenario of AI-based FER system by discussing their basic concepts, associated technologies, present challenges with some viable recommendations. However, some key takeaway can be:

- **Technological Foundation:** For successful application of FER techniques across industries like security, healthcare and marketing, the basement can be strengthened by computer vision, multi-modal techniques and deep learning methods.

- Ethical Grounding: The significance of ethical theories (utilitarianism, deontology, and virtue ethics) is highlighted through this discussion which can act as a guiding framework for further development of FER systems.
 - Privacy Concerns: The urgent need for accountable practices is underscored clearly by raising the concerns related to personal consent, data collection and storage, and surveillance.
 - Bias and Fairness: Performance inequalities and dataset imbalances across the variety of demographic groups portraiture serious threats of discrimination.
 - Psychological and societal impacts: FER systems can critically influence personal autonomy, trust in AI systems, and mental health, which can further result in vital social implications.
 - Legal frameworks: The existing guidelines, like CCPA and GDPR, may act as a partial safeguard, but the global loopholes and inconsistencies need to be considered on a serious note.
 - Mitigation strategies: For ethical acceptance of FER systems, bias-reduction methods, explainable AI, and privacy-preserving technologies play a major role.
 - Future Prospectus: Emerging technologies can open up the channels for new opportunities in exchange for robust research efforts, challenging interdisciplinary collaborations, and progressing risks.
-

8 Conclusion

The study of FER systems with the integration of AI conveys an influential yet ethically challenging complex intersection of human behaviours and advanced technologies. In the beginning, the significance of AI-based FER systems is highlighted with extended applications in crucial sectors like healthcare, education, and security. Then the fundamental concepts of FER systems and the available technologies are analysed to understand how the systems interpret human behaviours. Rapid adoption of this technology also demands a rigorous investigation of the ethical concerns, privacy aspects, and the available legal frameworks, which are also described. The common challenges circulating around the privacy and algorithmic bias, including demographic misrepresentation, fairness gaps, and unauthorized emotional surveillance, along with the societal and psychological concerns, are

thoroughly presented to raise awareness the users, policy makers, and developers. The urgent recruitments of global regulatory harmonization are pointed out to mitigate the risks of AI-based FER systems, and hence a set of suitable recommendations is stated to establish the importance of interdisciplinary research, trust in human-AI relations, and carry out further research for the smooth execution of this technology.

Finally, this can be noted that to serve humanity ethically and equitably, FER systems must be capable of bridging a linkage between accountability, innovation, and human dignity.

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Emotion AI: Challenges and Future Directions

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Abstract

The most richly diverse field of facial recognition is Emotion AI. This field builds a relationship between artificial intelligence and human emotional intelligence. Emotion AI applies identity recognition to decipher facial expressions, voice patterns, and even physiological signs to comprehend human feelings. This chapter explores the primary limitations and challenges of Emotion AI. It concentrates on data limitations and bias, technological challenges in implementing Emotion AI technology in real life, ethical hazards, and legal problems concerning trust in human and AI interactions. We use case studies and applications in health care, education, marketing, and public safety as a vehicle for illustrating the potential and risks associated with the use of these applications. We also stress the necessarily interdisciplinary nature of Emotion A.I., overlapping AI research with psychology, human computer interaction (HCI), and ethics.

and stewardship. We conclude by providing a roadmap based on future directions which highlight the importance of multimodal approaches (viz. AI deployment in an interdisciplinary manner), explainable and transparent architectures, culturally aware modelling, and sustainable practices. In combination with technical invention, an ethical consideration and human-centered practice of design, Emotion A.I. has the potential to develop/invest toward a transformative yet sustainable changes to human wellness and interaction across disciplines.

Keywords Face recognition – Artificial intelligence – Human computer interaction – Mental health – Emotion AI

1 Introduction

Emotion A.I., also known as affective computing, is an emergent area of research that identifies, accesses and responds to human emotions. Rapidly evolving beyond facial recognition, and multimodal data, Emotion A.I. moves toward a human-centered A.I. from simple identification, to understanding transient, sustained but complex emotional states [1]. In the context of the chapter, and consistent with a multidisciplinary and sustainable perspective, Emotion A.I. demonstrates the necessity to join the field of technical invention with psychological theory, ethical change, HCI, and stewardship. A person's facial expressions are still among the most efficient and informative sources for emotion detection. However, Emotion AI applications also typically combine this with speech, text, physiological signals, and indicators of context to create holistic understanding of human affect [2]. This chapter provides an overview of the technical, societal, and ethical challenges of Emotion AI, and suggest techniques for building systems that are ethical, take into consideration sustainability, and are accurate, inclusive, and cultural competent.

In more concrete terms, this chapter has multiple goals: First, we wish to present a clear and accessible summary of developments in research and practices of Emotion AI and facial recognition technologies; Second, we will analyze pertinent challenges related to multiple domains technical, ethical, social; Third, we will highlight the next priorities which balance innovativeness with sustainability. By drawing together concerns inter-

disciplinarily, our message is that real success in deploying using Emotion AI must consider an inter-disciplinary perspective to inform capabilities.

2 Foundations of Emotion AI in the Context of Facial Recognition

More generally, Emotion AI is about the use of computer-based facial recognition technology to do more than establish who a person is Shan et al. [3]. The identity verification mechanisms found in facial recognition systems, called person recognition systems, are focused on recognizing and mapping identity markers from facial features for identity verification. Emotion AI will use techniques and methods of person recognition for example, mapping facial expression over time that will result in quantifying changes in facial expressions linking them with possible emotional state. Emotion AI leverages facial signals to interpret emotional information through the analysis of subtle movements such as whether the user's eyebrows are raised, the extent to which the lip is curved, or various micro expressions [4]. The emphasis on facial data is of special importance, as the human face conveys more social information and is the most expressive form of communication modality.

However, effective recognition of emotion goes beyond simply being able to detect static facial points. It also requires a series of processes stemming from the original signals into reliable predictions. We can start with input modalities: visual facial data is often included alongside other sources, such as speech and physiological signals, to provide further contextual emotional meaning [5]. Next is feature extraction, which detects and identifies meaningful markers, such as facial action units that signify muscle movement, or prosodic features in speech, such as pitch and intensity [6]. Next, these features will move into the model architectures: deep learning nested architectures or convolution neural networks (CNNs) are typically used to explore spatial relationships within faces, whereas deep learning recurrent networks (RNNs), or transformer-based models, compartmentalize temporality in audio or physiological signals [7, 8]. The final path to journey is in the emotions' prediction, either mapping what is learned into discrete categories (e.g., happy, sad, or anger), or the continuous emotional dimensions of arousal and valence. Modern methods

increasingly utilize multimodal fusion frameworks as shown in Fig. 1. While facial recognition offers a powerful basis, the limits of facial expression alone still present some challenges since expressions may be masked, ambiguous, or culturally variable [9]. Multimodal systems address these drawbacks by utilizing a single architecture that encompasses facial, vocal, and physiological input to create a system that is more robust to contexts themselves [10, 11]. This approach allows the system to validate signals against each other for improved accuracy and resilience against real-world issues.

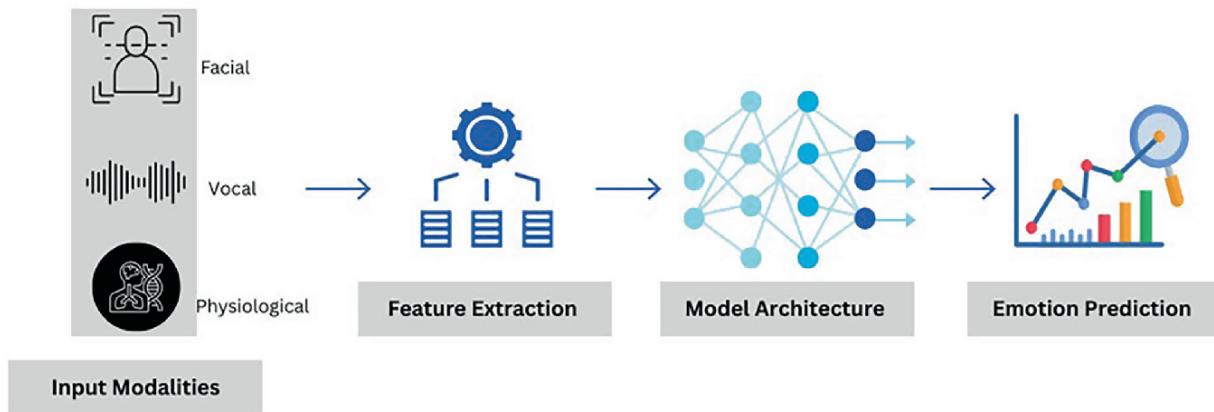


Fig. 1 Multimodal emotion AI framework

3 Multidisciplinary Nature of Emotion AI

The complexity of Emotion AI means it is reliant on the theories of many different disciplines. For example, artificial intelligence supplies the computational power to develop algorithms that can learn from facial, vocal, and physiological signals; psychologists and affective scientists ensure the development of models that reflect valid theories of emotion whether those theories are categorical (e.g., Ekman's basic emotions) or dimensional (e.g., valence-arousal models); ethics, law, and policy inform responsible, thoughtful development and application to ensure the absence of issues like privacy, bias, and misuses in cases of high stakes applications like surveillance or marketing and HCI is responsible for ensuring that systems are human-centered, accountable, and trustworthy while applying the same psychological and affective principles as well as consideration for how users perceive and interact with these emotionally intelligent machines [12]. Finally, sustainability and social sciences define longer-term

considerations, from the environmental cost of training the model to fair review across cultures and demographics [13]. Together, these perspectives provide a holistic framework for Emotion AI as illustrated in Fig. 2.

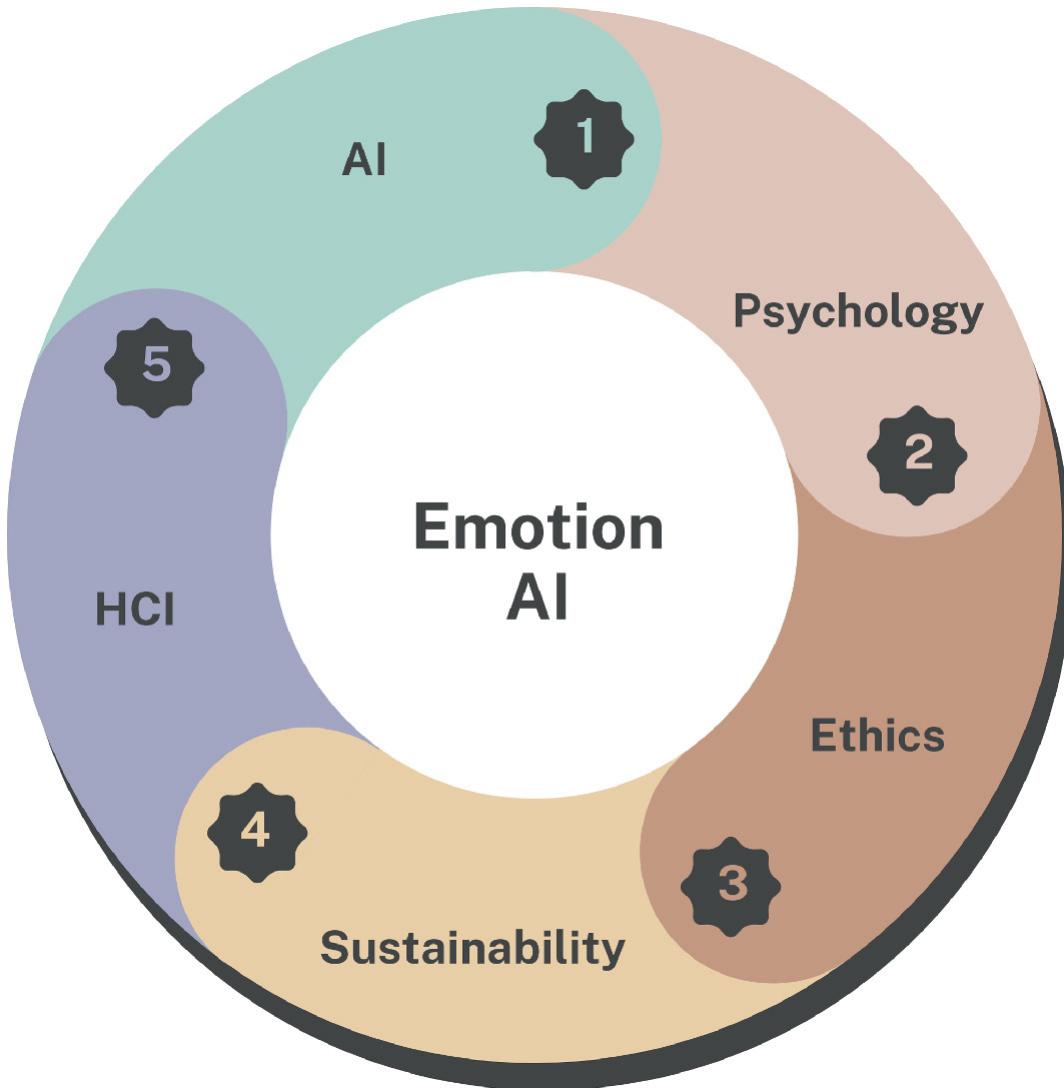


Fig. 2 Holistic architecture of emotion AI

Technical complexity is not enough, contextualizing in psychology ensures validity, ethics provides responsibility whereas HCI ensures usability, and sustainability ensures longevity [14, 15]. Without this integration, even technically accurate models risk social acceptance, ethical breaches, or environmental degradation.

4 Challenges and Limitations in Emotion AI

Even though the Emotion AI is significant, the task of creating it ethically and reliably is difficult by problems that lie far beyond algorithms and computing. This field of research combines technological innovation, human behaviour, and social ethics [16, 17]. Emotion AIs must work with limitations in their data, technical issues, and overarching ethical concerns if they must work equitably and effectively. Each of these aspects shows how the technology is based on the complexity of human beings at the same time, it provides both opportunities and a challenge of responsibility [18].

(1) Data-Related Challenges: The Foundation Problem

Emotion AI is highly reliant on the quantity and diversity of its data just like any other AI system [19]. People's emotions are by their very nature subjective, context-rich, and deeply personal characteristic, making collecting and labeling emotional data nearly impossible. One of the primary challenges of Emotion AI to overcome will be getting high-quality, large-scale datasets that truly represent the range of human emotional expression [20]. Existing datasets have mostly been collected from controlled laboratory settings where participants intentionally acted out emotions (not just expressive). Data like this creates a divide between what the Emotion AI learns on a dataset, and what it sees as emotions in real-life daily settings [21]. For instance, a model trained on extreme “happy” or “angry” faces of actors may not detect nuance in real settings, such as frustration or empathy.

Also, there are ongoing demographic and cultural disparities in many emotion datasets [22]. If most of your data comes from a small segment of a population, like western, younger, lighter-skinned individuals, the models trained on that data may be biased when deployed in diverse global populations. For example, across cultures the signs of facial expression can vary. A gracious smile is not necessarily going to show true happiness in a specific culture. Lack of cultural awareness could create misreading of emotion that will be important in use, such as in mental health tracking or educational settings where emotional issues and subtlety are important [23].

The subjectivity of labeling presents another confusing complexity, in contrast to objective subjective-based attributes such as temperature or sound frequency, emotions cannot be quantitatively measured [24]. Different human annotators might label the same facial expression or voice

clip differently, creating inconsistent ground truth data. Adding to the complexity of categorization, emotional states rarely function in neat categories someone might be both anxious and excited, but most datasets only impose rigid categories on that emotion. All this inconsistency adds up to measurement inconsistency, which undermines model reliability and applicability in the real world.

(2) Privacy and Ethical Data Collection

As the information contained within the data is highly sensitive, emotion AI introduces the most challenging privacy issues [25]. Most of data aims to assess diverse emotional states, in fact, concentrates on something apart from observers, observing facial expression or tone of voice. For instance, measuring basic or compound emotional states usually depends on heart rate variability or an EEG to record brain activity that may also yield some personal data regarding the individual [26]. Such information may be considered invasive if obtained without it being known or agreed upon. In cases of healthcare, or workplace monitoring, the essence of voluntary consent can be lost or even removed depending on what is done with emotional data. As an instance, a system of monitoring worker emotions to maintain productivity may utilize emotional data tagged with an individual's personal mental health [27]. The difficulty of gathering a data set large enough to maximize model performance/accuracy and the goals of keeping individuals' privacy is arguably one of the most ethically challenging issues in Emotion AI research. In addition to this, the physiological information such as EEG, heart rate variability, etc. provides yet another level of barrier to the problem [28]. Emotional states and even potential medical conditions can be inferred from signals as well, where abuse or compromise of this information is problematic. It is thus essential that privacy-preserving models, utilizing for instance, federated learning or differential privacy, are constructed to balance innovation with responsible ethical measures [29].

Apart from such data issues, Emotion AI systems face number of technical limitations when applied in real-world contexts.

Models constructed to quantify or evaluate emotion can work well in a controlled test set or lab “real world” test, catalogue or clinical environment but at times are vulnerable to “in-the-wild” environments where performance metrics can take a tremendous hit [30]. Utilization of

extraneous sources such as light fluctuations, facial occlusions, or noise can plague input signal and impact models such as, a camera-based emotion identification system can misunderstand an emotional event if the person is wearing a mask, specs or a headscarf. Speech-based evaluation face similar issues, apparent in we identify genuine emotional tone from varying pitch, accent, and ambient auditory cues [31].

In addition to this as we know human beings deduce emotional states emotion AI must be capable of multi-modal integration to ensure simultaneous application of facial, vocal, and physiological signals [32]. Each modality brings its noise and artifacts, but the added technical challenge is aligning the modalities in real-time. This challenge is exacerbated by issues when trying to interpret subtle or blended emotions like bittersweet feelings or repressed anger, which generally don't take on readily observable patterns.

Moreover, generalizability is a chronic problem, a model that has been trained on one dataset never seems to well for another context or population. If we talks about, an affect detection system trained on social media clips will never transfer to clinical environments [33]. This “domain gap” strengthens the limits of constructing models on finite and static data to quantify the dynamic, ever-changing nature of human affect.

(3) Ethical and Social Implications

Evidence created in a lab-type environment exceeds the societal and ethical implications of Emotion AI. There is more concern regarding misuse and manipulation with the possibility of social robots and affect detection being used to make inferences about very intimate states [34]. For instance, it is not far-fetched that Emotion AI would be utilized to monitor crowds and identify “suspicious” categories of emotions, patterns of interpretive behaviours which raise serious issues for civil liberties [35]. The prospects for governments or companies leveraging emotional data to manage, discriminate, or target behaviours build a definite need for robust ethical safeguards and compliance regulations.

Moreover, in any Emotion AI model biasness and discrimination can be quite simply imply instilled just to highlight, if an algorithm misjudges an emotion for specific demographic groups it can perpetuate stereotypes or produce unequal results [36]. A model that misinterprets anger in the facial

expressions of one ethnic group but Interprets calmness in another ethnic group sustains social stigma instead of improving it.

Another issue arises from emotionally influencing users in commercial and political situations. Advertising systems can take advantage of emotional vulnerabilities to customize ads for a certain mood or political campaigns can determine emotional states and respond to those in terms that impact human action [37]. These use cases indicate that ethical principles for transparency are necessary for the design of Emotion AI, to avert the potential for influencing human emotion.

(4) Trust, Usability, and Human–AI Interaction

Finally, trust and usability are continuing challenges for the human–AI relationship [38]. Emotion AI attempts to recognize human emotion and evoke a response, but the user questions whether a machine can truly “understand” emotion [39]. In situations where AI makes mistakes, for example, interpreting sadness as boredom—then the user no longer trusts the machine to accurately identify their emotion [40]. Conversely, some users may fall into the trap of overzealously trusting AI predictions, accepting its assessments regardless of whether the AI's prediction is wrong or the assessment is not appropriate to the context.

Moreover, these issues are complicated by a lack of transparency and explainability. Many Emotion AI systems function in a black box, providing predictions without understanding how the prediction was reached. In domains that are contextually sensitive, such as mental health or law enforcement, a black-box systems compromise accountability and generate ethical discussions [41]. It is paramount to generate Emotion AI that is explicable, inclusive of cultures, and centered on the user, and to involve not only engineers but interdisciplinary experts-psychologist, ethicists, and social scientists who are embedded in the real world-to contribute to solutions that honour the diversity of emotions with respect for the dignity of human [42].

(5) The Path Forward: Beyond Technical Fixes

The issues Emotion AI are making it evident that the future of Emotion AI should not always depend on better algorithms or including more data

[43]. These realities will not generate change. A human-centered approach must be included to have ethics, inclusivity, and transparency demonstrated when engineered or deployed [44]. Emotion AI should be in a context of respect to cultural differences, right to privacy, and accountability.

Ultimately, the target of Emotion AI should not be a replacement for human empathy, but a reformer and develop tools that to prepare us for the information of emotional experience, without losing sight of true ethics [45]. As researcher and developer begin to address technical, ethical, and societal challenges together and collectively, they have the potential to evolve Emotion AI into technology that is practically useful for humanity, not simply assessing it.

5 Case Studies and Applications

Emotion Artificial Intelligence, commonly referred to as affective computing, is fast transforming into one of the most exciting fields within today's technologies. Essentially, what this refers to is the idea of programming computers to be able to recognize and respond to people's emotions. Emotion AI observes things like facial expressions, tone of voice, heart rate changes, and even the pitch and rhythm of our speech to try and understand how we might be feeling in the moment and then adjust behavior accordingly [46]. It may sound preposterous and futuristic—but it is already becoming part of how healthcare, education, marketing, and even public safety are addressing specific issues. Each of these settings provides a slightly different instructive case—demonstrating not only what Emotion AI can perform, but also the ethical and social issues each antenna creates.

Case Study 1—Healthcare: Emotional Analytics for Mental-Health Support

Mental-health care relies heavily on emotion; therefore, Emotion AI has a natural place in this area. Traditional therapy is often built on what patients verbally share, and what clinicians see or observe about client emotion in a 60-min session [47]. Understandably, there is only so much observation can reveal about someone's emotional experience. A lot of people struggle with openly demonstrating their emotions. Newer generation Emotion AI systems are bridging that gap between observations and the emotional experience [48].

Emotion AI systems utilize computer-vision models, combined with voice analysis and physiological data monitoring to create a more continuous understanding of a patient's mood. A prominent illustration is Ellie [49]; a digital therapist developed at the University of Southern California. Ellie can conduct a conversation, while simultaneously tracking micro-expressions, eye movements and tone. In testing, members of the class talked much more freely to Ellie than to a human interviewer, which may have been because participants may not have felt judged by Ellie. This “openness” allowed clinicians to obtain data that would not typically be available behind social restraint.

In addition to the availability of virtual therapy platforms, wearable sensors can assess a number of physiological measures such as heart-rate variability or skin conductance, and transmit these data to algorithms designed to predict stress or anxiety [50]. If a patient is elevated over multiple days in a row, the system can notify a clinician, leading to early intervention. It would change how depression or PTSD and other mental health problems are tracked between appointments [51].

Not ignoring that the same characteristics that make these tools powerful can also make them sensitive. Emotional data points expose very personal parts of a person's life and mishandling them would destroy trust. Thus, developers must comply with applicable regulations, such as HIPAA or European GDPR [51], securely care of and properly storing that data, and explain how predictions come to their conclusions. Another underlying dilemma presents itself in cultural context. For example, a smile may communicate a person is simply being polite and does not signal happiness. Similarly, tears may represent frustration or joy dependent upon culture [52]. For emotion recognition to be ethically used in healthcare, it must be trained on large, diverse datasets and need to be interpreted by professionals who understand the nuances of people.

Case Study 2—Education: Emotion-Aware Learning Environments

Teachers and learners experience learning, teaching is an emotional experience [53]. A student's motivation, curiosity, or frustration typically determines how well they learn. Emotion AI can now provide educators with tools to detect these emotional cues to not only support learning, but to help make the classroom climate less stressful, especially in digital classrooms where full face-to-face contact is limited [52, 54].

Researchers at MIT created an Affective Tutoring System that uses webcams and physiological sensors to infer the learner's state of confusion, boredom, or engagement [55]. When the Affective Tutoring System infers confusion, it pauses to reintroduce new material or provide added hints; if it infers boredom, it could go into a mini-game or quiz to reengage. Teachers in face-to-face classrooms would make these same shifts instinctively, but online adjusted classrooms have not until now.

Other educational technology companies use sentiment analysis of student voices during an oral exam or group discussion [56]. If a student's tone indicated hesitation or anxiety, it could either allow for sense feedback or a calming exercise to ground the student before continuing. For students diagnosed with autism or other neurodivergent dispositions, it could help in understanding their own emotional cues.

Although it has great potential, monitoring emotions in classrooms creates ethical dilemmas [57]. Even monitoring students continuously would feel less than ideal, and not to mention, students may change their behavior just because they are being monitored. Also, not everyone will make the same interpretations as a result of the same facial/vocal patterns. For instance, a child who is thinking might appear "disengaged" to an algorithm that is looking for eye contact. Educators should always treat the outputs of Emotion AI as indicators and refrain from making absolute conclusions, and always apply human empathy into the equation of teaching [58].

Case Study 3—Business and Marketing: Understanding the Customer's Heartbeat

In business, emotions often drive decisions, more than logic does. Businesses have always been capturing customers' feedback by sending surveys, or conducting focus groups to capture customer satisfaction, but those capturings depend on what the customers want to say or can say [59]. Whereas Emotion AI offered something ultimately new insight based on authentic, in-the-moment, responses.

One case in point is Coca-Cola [59]; which, used facial-expression-analysis software to test how advertisements impacted viewers. The cameras quickly scanned the audience, capturing their spontaneous facial expressions of smiles or frowns while viewing a Coca-Cola advertisement. The researchers discovered which scenes generated authentic amusement

and which scenes generate boredom and modified their advertising accordingly [60]. Other retailers use similar systems to gauge an in-store shoppers facial expression as they browse products or respond to virtual assistance system.

Emotion AI can also function within customer service agents. For instance, voice-analysis system can aspire to detect irritation or relief from customers during support calls [61]. The technology may allow chatbots to adjust their tone or transfer an upset caller to a live agent. Some companies use this technology as an internal mechanism and apply emotion analytics to group meetings and conversations to track collective morale; however, they create their own potential privacy risks.

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Case Study 4—Public Safety: Between Security and Civil Liberties

The most contentious use of Emotion AI appears to be in the area of public safety. Policeman, and public safety employee has always had a vision of systems that can read emotional readings from crowds or group events to identify potential threats [63]. In this way cameras could identify nervous or aggressive personalities from an airport queue, and alert security systems.

In theory, technology of that nature could not only prevent violence, but also reduce risks in times of crisis working effectively. Crowd-emotion monitoring, for example, could be employed to measure growing panic during a stampede or generate a corresponding reaction with protests or demonstrations [64]. But such possible uses are marred with ethical problems in real life, since emotions tend to be indeterminate; merely witnessing somebody with anxiousness doesn't necessarily show guilt, nor does a person displaying anger imply a propensity to provoke violence.

Also, in public places, citizens may not have the ability or opportunity to provide informed consent for emotional surveillance [65]. A constant analysis of facial cuts may result in individuals feeling as though they are being surveilled not because of their actions, but because of their manners,

which could lead to tensions a topic counter to democratic freedoms. To safeguard against atrocious use, governments must exercise control by using strict regulation towards governments emotional data algorithms, independent technologies and processes for oversight, and available practices that outline when and how emotional data could be collected or stored [66]. In the absence of this regulation, the cost of the perceived safety and the daily experience of a citizen may result in negatively altering the perception of privacy.

Connecting the Case Studies: Common Threads and Cautions

When combined, these case studies show both the scope and complexity of the use of Emotion AI. As a reminder, in healthcare, it allows doctors into their patient's experience. In educational settings, it fosters tailored learning environments for success. In business eats it creates insights into their customer and use [67]. In public safety, it creates an early warning for the dangers of the environment [68]. Yet all four speak to the same truth, which is that technology sophisticated does not guarantee positive conversion on social engagement.

The successful uptake of Emotion AI rests on transdisciplinary collaboration. Computer scientists can advance accurate models and algorithms, but they require psychologists to decode the signals of emotional expression and affect; ethicists to asses whether the outputs are fair; and policy experts and practitioners to constrain the relationships and the responsible actions of machines in a constructed national order [69]. Likewise, inclusive and culturally aware training data, transparent models and algorithm, and HITL systems can act as safeguards contained in algorithmic systems.

Similarly, the notion of explainability is present in all four cases. If AI determines to you that someone is anxious or happy, the individual receiving the information, and the observer, should have an understanding of how the AI knew that. It is the only way to build trust in an explanation, and to allow a person to dispute it or challenge it. Indeterminate machines, even with exceedingly high accuracy, can be rejected when they don't explain their rationale.

Emotion AI is a remarkable intersection of technology and the human experience, demonstrating machines can be designed to not only compute, but sense, listen, and respond with a degree of authentic, emotional

intelligence [29, 70]. The applications are systematically organized and quite expansive, from surveillance that detects early warning signs of depression or increase engagement in the classroom or areas like customer sentiment. Nevertheless, every case after case serves as a reminder of the deeply personal, subjective nature, and cultural layers of emotional experience.

If Society want to promote ethical progression, they needs to treat Emotion AI as a collective human endeavor rather than a strictly technical one. The most valuable systems will be accurate but transparent, they will be powerful but more attentive towards privacy considerations, and innovative but with respect to ethical constraints [71]. Only with these considerations in mind can Emotion AI improve human experience by allowing machines to understand us without narrowing the very humanity we value.

6 Future Directions for Emotion AI

The Emotion AI should still focus on making use of ethical, human-centered, and long-term strategies even while contributing to maintain technological advancement. The realization of emotion recognitions from facial, vocal, physiological, or textual signal to improve robustness and validity given changing real-world contexts necessitated technical advancements in context-aware and multi-modality emotion recognition techniques. The transition to real-time usage would be made simpler as well as the negative effects on the environment would be reduced if the frameworks and model structure were computationally light and energy efficient. To provide end users trust and transparency it offers some interpretation and insight into model predictions and boundaries, emotion recognition systems must incorporate explainable AI methods. The establishment of guidelines and policies regarding data privacy, bias, and accountability will also assist in ensuring that it is developed and implemented appropriately, that will reduce misuse and biasness. Ethical and regulatory avenues are equally essential. By incorporating aspects of psychology, neuroscience, human–computer interaction, the social sciences, and policy studies to create systems that are not only technically feasible but also socially justifiable, cross-disciplinary collaboration will continue to be essential to these future endeavours. Next-generation emotion AI

solutions will be human-centered and responsible in their upcoming innovations, but they will also socially influence sustainability toward solutions for enhanced wellbeing, engagement, and human–machine teaming in most areas of life.

7 Conclusion

Emotion AI combines a case study for the fusion of technical innovation and human-centered design. It succeeds not only based on algorithms sophistication but also on attention to the psychological theory, moral standards, HCI principles, and sustainability factors throughout development. This dedicated chapter has contended with significant tensions, provided examples that indicates challenges from the real world, and hinted at future directions in the form of ethical, inclusive, and effective advice for Emotion AI deployment. Grounding a multidisciplinary perspective, can bring richness to human–machine interaction, aid in the promotion of mental health, customize education, and offer social benefits in future applications without nonetheless compromising on ethics and social deficits related to AI technology.

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