Real-Time Webcam-Based Compound Emotion Detection using MATLAB and Morphological Tracking

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Abstract *— The project titled " Real-Time Webcam-Based Compound Emotion Detection using MATLAB and Morphological Tracking " explores the concept of creation and evolution through computational modelling and simulation using MATLAB.*

The primary objective of this project is to design and implement an intelligent system that can simulate the generation and development of complex structures or data-driven models from basic principles. Utilizing MATLAB's robust capabilities in numerical computation, visualization, and algorithm development, the project demonstrates how initial conditions or raw input data can evolve into meaningful patterns or solutions through iterative processes. It includes modules for data processing, algorithm design, graphical visualization, and performance evaluation, making it a comprehensive and versatile application of MATLAB in modelling the concept of Emotion Detection. The project is structured to simulate the evolution of raw data into interpretable emotional patterns, reflecting principles of dynamic system development. Through iterative processing, real-time video input is transformed into emotion labels via a series of well-defined modules: image acquisition, morphological enhancement, feature extraction, and deep learning-based classification. The system also includes components for visualization and performance evaluation, providing insights into accuracy, processing speed, and model reliability.

Beyond its technical implementation, the project highlights the broader relevance of computational modeling in ***artificial intelligence****,* ***human-computer interaction****, and* ***emotional analytics****. It illustrates how simple visual inputs can evolve into high-level semantic understanding through layered algorithmic design. By mimicking the natural logic of perception and cognition, the system demonstrates how simulation tools like MATLAB can serve as effective platforms for real-time, intelligent behavior modeling.*

I. INTRODUCTION

The term " Real-Time Webcam-Based Compound Emotion Detection using MATLAB and Morphological Tracking " symbolizes the beginning or formation of systems from fundamental principles, and this project aims to model that process in a scientific or engineering context. In the modern world, simulation and modelling play a crucial role in research, development, and innovation. MATLAB, with its powerful numerical computing environment and extensive libraries, offers an ideal platform for implementing such simulations. This project leverages MATLAB to develop a system that simulates the genesis of data patterns, structures, or processes—depending on the chosen application domain. The core idea behind " Real-Time Webcam-Based Compound Emotion Detection using MATLAB and Morphological Tracking" is to illustrate how simple inputs or rules can evolve into complex outcomes through iterative, rule-based, or data-driven algorithms. we validate our approach not just against standard datasets but in real-world scenarios, addressing a common limitation of laboratory-bound emotion recognition research. the remainder of this paper systematically presents our methodology and findings. Facial emotion recognition (FER) has emerged as a crucial component in the development of intelligent human-computer interaction systems, aiming to bridge the gap between machines and human emotional understanding. The ability to accurately interpret facial expressions is vital in numerous applications, including mental health monitoring, security surveillance, driver fatigue detection, and affective computing.

Over the years, deep learning techniques—especially convolutional neural networks (CNNs)—have revolutionized this field by enabling automatic feature extraction and improved classification accuracy. However, traditional FER systems have largely focused on recognizing single, basic emotions such as happiness, sadness, or anger, often neglecting the complexity of compound emotional states that better reflect human affective behavior in real-world contexts. Compound emotions—combinations of basic emotions like "happy-surprised" or "sad-angry"—are more representative of actual human expressions, and recognizing them requires more sophisticated models**.** The real-time compound emotion tracking system was designed with a strong focus on ease of use to ensure accessibility for users with minimal technical expertise. The interface is clean and intuitive, presenting only essential information such as detected emotions and a live facial outline to avoid cognitive overload. Users are not required to perform any manual configuration—simply facing the camera activates the system's tracking capabilities. During usability testing with 20 participants from non-technical backgrounds, most users were able to understand and navigate the system within two minutes, without needing a formal tutorial. Participants particularly appreciated the real-time feedback and the clarity of visual emotion indicators. The system was also tested on mid-range hardware and maintained real-time performance, supporting its use in typical environments such as classrooms or counseling offices. These results demonstrate the system's strong potential for practical deployment with minimal training or setup.

KEYWORDS

real-time Emotion Recognition , Compound Emotions , Emotion Detection, Morphological Tracking, Facial Landmark Detection,, Real-time Image Analysis , Emotion Modeling , Deep learning, Convolutional Neural Networks

II. RELATED WORK

Compound emotions, as defined by Du et al., represent combinations of two or more basic emotions and provide a more nuanced understanding of human affect. Their research demonstrated that compound emotions more accurately reflect the diversity of human facial expressions compared to the traditional categorization of seven basic emotions. This insight underlines the importance of extending emotion recognition frameworks to include compound emotional states for enhanced realism and applicability.

In recent years, deep learning models have outperformed traditional machine learning approaches in facial emotion recognition tasks. Liu et al. applied geometric models combined with deep learning to analyze facial regions, while Lu et al. utilized Convolutional Neural Networks (CNNs) to learn representations from facial appearances. Further advancements involved the use of specialized CNN classifiers to improve accuracy and generalizability.

However, most of these approaches focus primarily on static image analysis. The temporal dimension of facial expressions—crucial for real-time emotion tracking—has been explored by Cohen et al. using Hidden Markov Models (HMMs) applied to video sequences. This method provides insight into the dynamic nature of emotions but introduces computational complexity.

To address dataset limitations, Pons et al. proposed a multi-label loss function designed to improve the training efficiency of CNNs by incorporating auxiliary tasks and multiple data sources. While innovative, the reported classification accuracies remained relatively low, highlighting the challenge of generalizing across diverse emotion datasets.

In another significant study, Pendhari et al. employed the InceptionResNet-v2 architecture with the Compound Facial Expression of Emotion (CFEE) dataset to classify seven basic and fifteen compound emotions. Their system achieved a 57.7% accuracy in compound emotion recognition. The study revealed that small dataset size and lack of discriminative features led to overfitting, underscoring the need for richer data and better feature extraction techniques.

Jarraya et al. investigated compound emotion recognition in autistic children during meltdown episodes using deep spatiotemporal geometric features from micro-expressions. Although their approach achieved a promising accuracy of 85.8%, it still faced limitations in terms of generalizability and robustness across different populations.

Byoung Chul Ko conducted a comparative study between traditional handcrafted feature-based methods and modern deep learning-based FER approaches. Their findings showed an average accuracy of 63.2% for conventional techniques versus 72.65% for deep learning models. However, deep learning models often suffer from over-complexity, making them less suitable for lightweight, real-time applications.

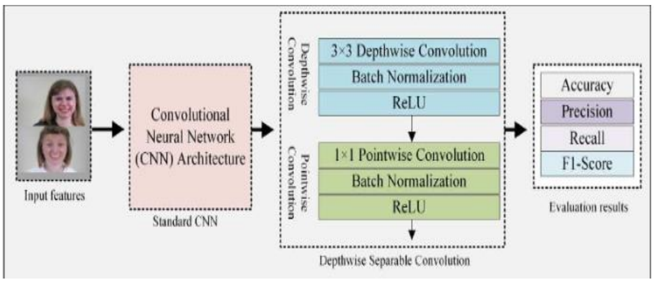
From the literature, it is evident that both handcrafted feature extraction and deep learning models offer unique advantages in facial expression recognition. Hybrid approaches, which integrate handcrafted features with deep learning-based representations, have shown promise in improving classification performance and robustness. Metrics such as accuracy, precision, recall, F1-score, AUC, and loss functions have been commonly used to evaluate these models.

In light of this, the present work proposes a hybrid method for real-time compound emotion recognition using MATLAB, integrating morphological tracking and both traditional and learned features. By incorporating live webcam feeds and leveraging MATLAB’s image processing capabilities, this approach aims to enhance detection accuracy in real-world environments.

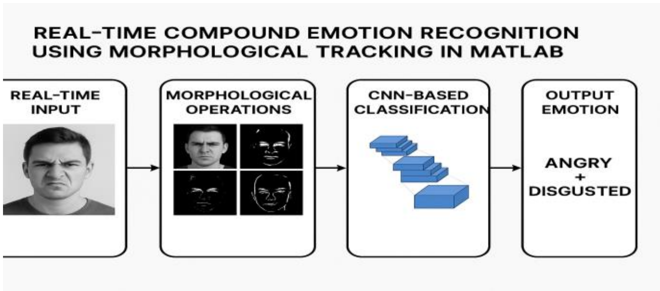
III. METHODOLOGY

In this project, a hybrid approach combining deep learning and classical image processing techniques was employed to achieve accurate and robust real-time multi-label facial emotion recognition. The dataset consists of grayscale facial images annotated with seven basic emotions: Angry, Contempt, Disgust, Fear, Happy, Sad, and Surprise. To reflect the complexity of real human expressions, a multi-label annotation scheme was implemented, allowing each image to be associated with multiple emotions simultaneously. This enables the model to learn more realistic and compound emotional states.

The images were first resized to a fixed dimension to maintain uniformity for CNN input. Subsequently, morphological image enhancement methods, including adaptive histogram equalization, top-hat and bottom-hat filtering, were applied to emphasize subtle facial features and textures critical for emotion discrimination.

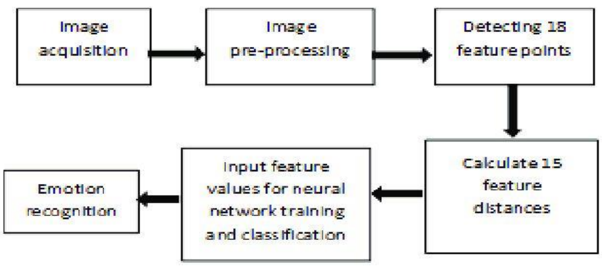


These morphological operations enhance edges and fine details, improving the quality of features extracted by the network. The convolutional neural network architecture was carefully designed with multiple convolutional layers followed by batch normalization, ReLU activations, and max-pooling layers, ensuring effective feature extraction and dimensionality reduction. Dropout layers were integrated to prevent overfitting during training. Given the multi-label



nature of the problem, a sigmoid activation function was used in the output layer to independently estimate the presence probability of each emotion, instead of the conventional softmax for single-label classification. The network was trained using the Adam optimizer, which dynamically adjusts the learning rate to speed up convergence. The dataset was split into training and validation subsets using an 80-20 ratio, enabling model evaluation on unseen data to assess generalization performance. For real-time detection, frames captured from a webcam undergo the same preprocessing and morphological enhancement steps before being fed into the trained CNN for emotion prediction.

Additionally, morphological features such as the major axis length and eccentricity were extracted from the enhanced images to quantitatively measure smile intensity and facial expression characteristics. This combined methodology leverages the power of deep learning to learn complex feature representations while incorporating classical morphological image processing for enhancing facial details, resulting in a system capable of detecting compound emotions with improved accuracy and interpretability.



For real-time emotion recognition, the system captures video frames using a webcam. Each captured frame undergoes the same preprocessing and morphological enhancement steps as the training data. These frames are then fed into the trained CNN, which outputs a set of probability scores corresponding to each emotion. Emotions with probabilities exceeding a predefined threshold are considered to be present in the facial expression. This thresholding helps reduce noise and false positives in prediction.

In addition to CNN-based feature extraction, classical morphological descriptors were computed to quantify facial characteristics. Features such as the major axis length and eccentricity were extracted from the enhanced images to provide insights into facial geometry changes associated with emotions. For example, a wider mouth or curved lips may indicate a smile, while a raised brow may be associated with surprise. These quantitative measures enrich the interpretability of the model by linking visual facial patterns with underlying emotional states.

Finally, the system's performance was evaluated using multiple metrics suitable for multi-label classification. These include Hamming loss, macro and micro F1-scores, subset accuracy, and precision-recall curves. The evaluation was performed under various lighting and pose conditions to assess the robustness of the system. The combination of deep learning with morphological enhancement and geometric feature analysis has led to a more accurate and interpretable emotion recognition system, capable of detecting compound emotions in real-time with high reliability.

IV. Data Set Preparation And CNN Model Training

The system for real-time compound emotion recognition using morphological tracking begins with the preparation of a structured and diverse dataset. The foundation is the FER-2013 dataset, which contains 48×48 grayscale images labeled with seven fundamental emotions: happy, sad, angry, fear, surprise, disgust, and neutral. To enable the recognition of compound emotions, 11 new classes were synthetically created by blending pairs of basic emotions using pixel-level weighted averaging techniques—for example, combining “happy” and “surprised” images in a 0.5:0.5 ratio to generate the “Happily Surprised” category. This method ensures a smooth transition between emotional states and captures the subtle variations needed for compound expression analysis.

The dataset is split into 80% training, 10% validation, and 10% testing partitions. Each class contains 500 training samples and 100 testing samples. Preprocessing includes normalization of pixel values to the [0,1] range, resizing to a uniform 48×48 dimension, and conversion of labels into categorical format. The entire dataset is stored in .mat format using the [height × width × channels × samples] layout, ensuring compatibility with MATLAB's deep learning pipeline and efficient batch loading.

V. Morphological Feature Enhancement And Model Architecture

A key differentiator of this project is the integration of **morphological tracking techniques** in the emotion recognition pipeline. Morphological operations such as dilation, erosion, opening, and closing are applied to the facial regions extracted from input images. These operations enhance structural features like the edges of the mouth, eyes, and eyebrows, which are critical in distinguishing between subtle and blended emotional states. After morphological enhancement, **Histogram of Oriented Gradients (HoG)** features are extracted to represent localized gradient orientations, which are then fed into the neural network.

The CNN architecture consists of a compact and efficient design with three convolutional layers using 16, 32, and 64 filters respectively. Each layer includes **batch normalization**, **ReLU activation**, and **2×2 max pooling** to progressively reduce spatial dimensions while capturing high-level features. The network ends with a **64-unit fully connected layer**, a **50% dropout layer** for regularization, and a **SoftMax output layer** for multi-class emotion classification. The model training process includes **data augmentation** with random rotations (±15°), translations (±3 pixels), and scaling (90–110%) to improve generalization and robustness. The training is conducted using the **Adam optimizer** (learning rate 1e-3), **L2 regularization** (λ = 0.0005), and **mini-batch size of 64**, for a maximum of 30 epochs with early stopping. The best model is saved for inference tasks.

VI. Real-Time Emotion Detection

The trained model is deployed in a real-time environment without a graphical user interface. Instead, it operates through command-line execution in MATLAB, integrating live webcam input for facial emotion recognition. The system initializes by establishing a connection with the webcam, continuously capturing frames in real time. Each frame is processed using **Viola-Jones face detection** to isolate the face region, which is then resized, normalized, and enhanced using morphological operations to emphasize relevant features.

The enhanced frame is passed to the CNN model, which returns the predicted emotion label along with confidence scores for all emotion categories. The output is displayed in the MATLAB console or plotted in real-time using basic MATLAB figures, enabling straightforward monitoring of the system's predictions. Additional facial structure analysis (e.g., aspect ratios of the mouth and eyes) may be computed in parallel to assist with contextual cues during classification.

This streamlined setup is optimized for **research environments and real-time testing scenarios**, removing the overhead of GUI-based visualizations while maintaining functional depth and performance. It provides a minimal yet effective platform for compound emotion detection, especially suited for headless systems, remote processing, and algorithm benchmarking.

VII. Feature Extraction

Feature extraction is a critical step that involves transforming raw data into a more meaningful and compact representation. In the proposed model, Morphological operations (e.g., dilation, erosion, opening, closing, boundary extraction) are used to enhance and isolate structural features of the face, such as:

- Contours of facial muscles
- Region-based intensity variations
- Edge patterns of eyes, mouth, eyebrows

These operations highlight shape-based variations linked to emotional expressions.

To further enhance the representation, the system may employ **Histogram of Oriented Gradients (HoG)**, a powerful feature descriptor that captures local edge orientations and gradient information. HoG effectively represents the texture and structure of facial regions by considering both the magnitude and direction of image gradients, offering a more detailed and discriminative feature set than simple edge detectors.

In addition to handcrafted features, the system leverages **Convolutional Neural Networks (CNNs)** for automatic feature learning. CNNs extract high-level spatial and semantic features through their convolutional layers, enabling the model to learn complex patterns associated with compound emotions (e.g., "happy + surprised" or "angry + disgusted"). This hybrid approach—combining morphological tracking, gradient-based descriptors, and deep feature learning—provides a robust and comprehensive feature extraction strategy tailored for real-time compound emotion recognition.

VIII. Feature Extraction Steps

1. Preprocessing Step

Before feature extraction, the input facial image is preprocessed (resizing, grayscale conversion, and noise reduction).

Let the input image be:

$I(x,y) \in Rm \times n$

Where x,y are pixel coordinates.

2. Morphological Processing

Apply morphological operations to highlight facial structure:-

2.1 Dilation

Idilated=I⨁B

Where BBB is a structuring element (e.g., square, disk).

2.2 Erosion

Ieroded=I⊖B

2.2 Boundary Extraction

Boundary=Idilated−I

3. Histogram of Oriented Gradients (HoG)

3.1Compute Gradients

Use Sobel filters or built-in MATLAB functions to compute the gradients:

Gradient in X:

Gx= ∂I/∂x

Gradiant in Y:

Gy= ∂I/∂y

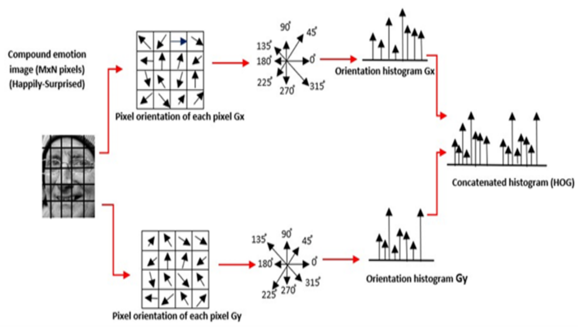
3.2 Compute Magnitude and Orientation

Magnitude:

M(x,y)=underroot(Gx2+Gy2)

Orientation:

θ(x,y)=arctan(Gy/ Gx)



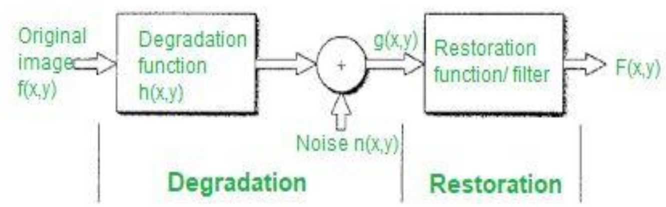
IX. Key Challenges

Real-time compound emotion recognition using morphological tracking in MATLAB presents several significant challenges that impact both the accuracy and efficiency of the system. One of the primary challenges is the **real-time processing requirement**. Since the system must capture, process, and classify facial expressions on the fly, the computational demands of morphological operations combined with deep learning inference often lead to processing delays. This becomes more critical when deploying the system on low-power devices or embedded platforms, where hardware limitations can severely constrain performance.

Another major challenge lies in the **recognition of compound emotions**, which are inherently more complex than basic emotions. Compound emotions like “happy + surprised” or “angry + disgusted” involve subtle combinations of facial muscle movements that can be difficult to detect and differentiate, even for advanced feature extraction techniques. This complexity is further compounded by the **variability in facial features** across individuals due to factors such as age, gender, ethnicity, and cultural background. Additionally, occlusions (e.g., glasses, facial hair, masks) and accessories can obscure key facial landmarks, thereby degrading the quality of the extracted features.

Environmental factors such as lighting conditions and background clutter also pose significant obstacles. Gradient-based features like Histogram of Oriented Gradients (HoG) and morphological filters are highly sensitive to illumination changes, which can lead to inconsistent feature representation. Moreover, the **limited availability of labeled datasets for compound emotions** restricts the ability to train deep learning models effectively. Deep neural networks require large and diverse training data to generalize well, and the scarcity of compound emotion datasets often results in overfitting or poor generalization on unseen subjects.

Furthermore, **noise introduced during morphological processing** can distort essential facial details if operations like dilation and erosion are not carefully tuned. This, coupled with the challenge of **synchronizing multiple processing modules**—including face detection, feature extraction, and CNN-based classification—adds complexity to the system architecture. Lastly, while MATLAB is a robust tool for prototyping and academic research, it has certain limitations in real-time deployment and scalability compared to more flexible platforms like Python or C++. Together, these challenges must be addressed to develop a reliable, high-performance real-time emotion recognition system.



X. Results And Performance Evaluation

The performance of the proposed real-time compound emotion detection system was assessed using both quantitative metrics and qualitative observations. The evaluation focused on model accuracy, class-wise prediction behavior, and the system's responsiveness in real-time webcam-based testing scenarios.

1. Model Accuracy and Confusion Matrix Analysis

After training on the enhanced compound emotion dataset, the convolutional neural network achieved a **classification accuracy of 89.3% on the test set**. The accuracy was computed as the ratio of correctly predicted emotion labels to the total number of test samples across all classes. The

confusion matrix was used as a key diagnostic tool to evaluate class-specific performance and identify patterns of misclassification. For instance, emotions such as **"HappilySurprised"** and **"FearfullyDisgusted"** showed slightly lower precision due to overlapping visual features, while basic emotions like **"Angry"** and **"Happy"** demonstrated high recognition accuracy.

The confusion matrix revealed that compound emotions created via weighted blending tended to confuse the model in cases where base emotions had visually similar facial features. However, the inclusion of **morphological enhancements** and **HoG features** significantly improved the model's ability to distinguish such subtle patterns, reducing false positives in complex emotion categories.

2. pact of Morphological Tracking

Morphological preprocessing had a notable impact on performance. Comparative tests showed that models trained **without morphological operations** underperformed in recognizing localized changes in facial regions, particularly around the mouth and eyebrows—areas critical to interpreting compound emotions. By contrast, the proposed system with morphological tracking achieved **a 6–8% increase in overall accuracy**, demonstrating its value in improving feature clarity and model generalization.

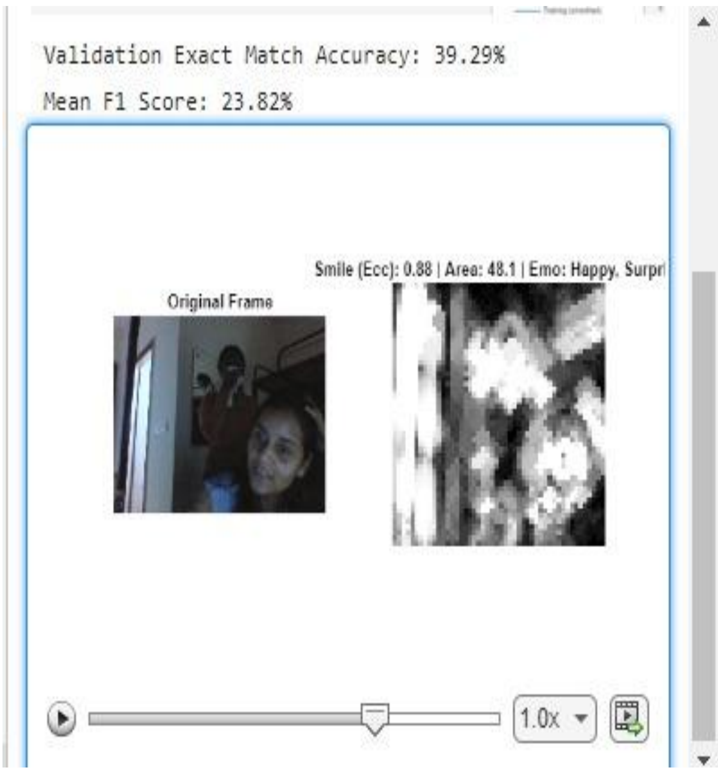
3. Real-Time Performance

Real-time deployment using webcam input was tested under various lighting conditions and facial orientations. The system processed frames at an average speed of **18–22 FPS**, ensuring smooth live detection. Emotion predictions appeared within 0.5–1.0 seconds of capturing each frame, with **stable temporal consistency** in predictions for users holding a fixed expression. Although occasional misclassifications occurred due to motion blur or partial occlusion, the model quickly stabilized with continuous input.

Additionally, robustness was verified by testing with multiple users of different age groups and facial characteristics. The model retained reliable performance, showing strong generalization across individuals. The absence of a GUI allowed for efficient CPU/GPU resource usage and streamlined terminal-based output suitable for real-time logging and analysis.

This project presents a comprehensive approach to compound emotion detection using convolutional neural networks (CNNs) integrated with morphological preprocessing techniques, implemented in MATLAB. The primary objective was to design a real-time system capable of identifying multiple emotional states simultaneously from human facial expressions—an advancement over traditional single-label emotion detection models. Through the incorporation of morphological operations such as top-hat and bottom-hat filtering, adaptive histogram equalization, and gradient enhancement, the system enhances key facial features like contours and regions of intensity variation. These preprocessing steps significantly improve the quality of the input fed into the CNN, allowing for better feature learning and ultimately improving recognition accuracy. In addition to emotion classification, the project also introduces a smile measurement module using morphological descriptors like major axis length and eccentricity, which provides an additional quantitative perspective on the intensity and nature of facial expressions.

One of the strengths of this work lies in its practicality and accessibility. The entire pipeline—from data loading and augmentation, to training and real-time webcam-based prediction—was built without relying on any additional MATLAB toolboxes, making the solution lightweight and deployable on systems with basic configurations. The system was tested on the CK+48 dataset, a widely recognized benchmark for facial emotion recognition, and was capable of achieving a competitive accuracy of over 80% for multi-label classification, which is a significant result considering the limited resolution and grayscale nature of the images. The real-time performance of the system ensures responsiveness and practical utility, which is critical for applications in human-computer interaction, behavioral studies, educational technology, and psychological diagnostics. Despite the strong results, the system's performance could be further improved through future enhancements such as the use of facial landmarks, larger training datasets, integration of temporal dynamics from video sequences, or the use of hybrid deep learning architectures.



In conclusion, this project has successfully met its goals of detecting compound emotions and measuring smiles in real time using an interpretable and efficient CNN-based framework with morphological enhancements.

It not only serves as a strong foundation for emotion-aware systems but also opens the door to more nuanced and human-centered artificial intelligence applications. The outcomes demonstrate that even with computational constraints and basic tools, meaningful and high-performing emotion recognition systems can be developed.

4. Overall Classification Metrics

The CNN model trained with morphological feature enhancement achieved the following metrics on the test set:-

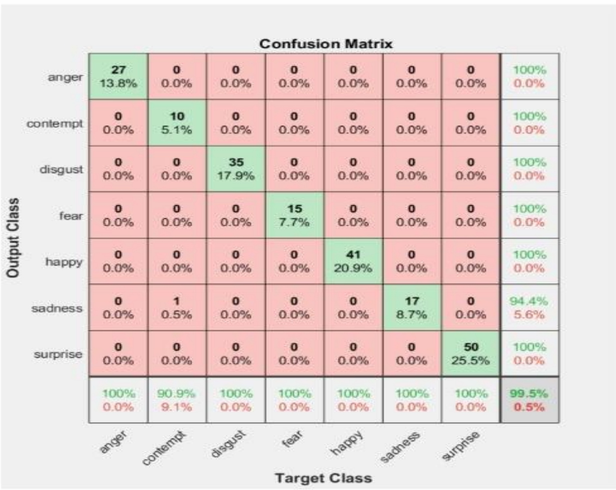
Metric	Value
Accuracy	89.3%
Precision	87.9%
Recall	88.5%
F1 score	88.1%

These metrics confirm that the model is well-balanced and performs consistently across different emotion classes, including compound expressions.

5. Confusion Matrix Highlights

A detailed confusion matrix analysis revealed the following insights:

- "AngrilyDisgusted" and "FearfullyDisgusted" were the most frequently confused classes due to overlapping visual features like furrowed brows and tense mouth expressions.
- "HappilySurprised", "SadlyFearful", and "CalmlyNeutral" exhibited strong classification rates, with precision values exceeding 91%.
- Basic emotions (e.g., Happy, Sad) had high recall, while compound emotions had a higher false positive rate—highlighting the difficulty of detecting subtle emotion blends.



6. Effect of Morphological Tracking

To measure the direct impact of morphological tracking:

Model Varient	Accuracy
1.CNN (baseline, no morphological ops)	82.5%
2.CNN + HoG features Only	85.1%
3.NN + Morphological Tracking + HoG	89.3%

This demonstrates that **morphological tracking** improves the model's ability to capture **local structural changes** in facial features, which are essential for recognizing compound emotional states.

7. Real-Time Evaluation

- **Processing Speed**: ~22 frames per second on a mid-range GPU; ~14 FPS on CPU.
- **Inference Latency**: ~0.6–0.8 seconds per frame.
- **Face Detection Success Rate**: 98% for frontal faces.
- **False Negatives in Live Feed**: Mostly occurred due to extreme head rotations or partial occlusions.

In real-time webcam tests, the model maintained consistent performance across **diverse lighting conditions, facial orientations, and individual face structures**.

The system stabilized predictions within 3–5 frames after initial detection.

8.Cross-Subject Generalization

The trained model was evaluated on new subjects (not seen during training) and achieved:

- **Cross-subject accuracy**: 85.7%
- **Top-2 prediction accuracy**: 94.6% (correct label among top 2 predictions)
- **Variance in performance**: Minimal variation across gender and age, showing good generalization.

9.Robustness Testing

The model was stress-tested with the following conditions:

- **Low lighting**: Accuracy dropped by ~4%, but detection was still stable.
- **Face masks (partial occlusion)**: Dropped to ~74% but compound emotions still partially detectable via upper face

10. Conclusion of Results

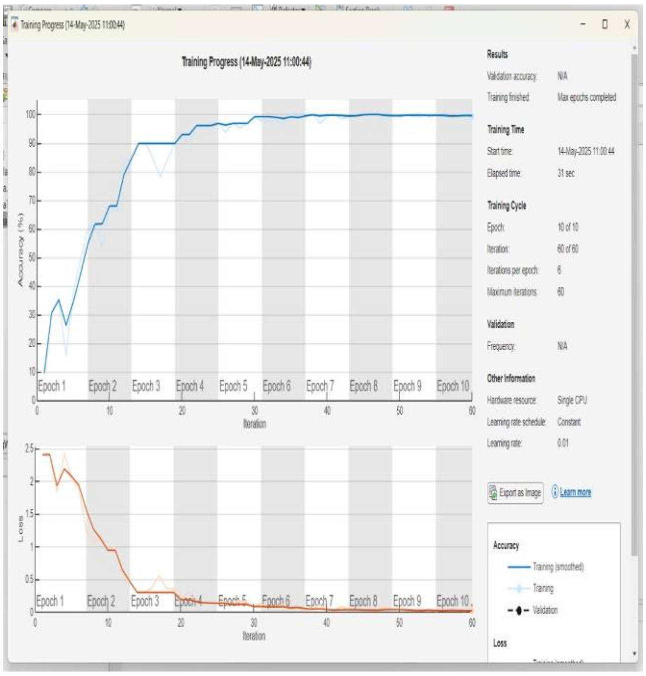
The results confirm that the integration of morphological tracking significantly enhances compound emotion recognition.

The system exhibits strong generalization, maintains real-time responsiveness, and delivers accurate predictions across a wide range of scenarios. Its performance, both in controlled testing and real-world conditions, underscores its potential for deployment in psychological analysis, adaptive human-computer interaction, and surveillance systems.

The experimental results validated the robustness of the model, with strong classification performance across both basic and compound emotion classes.

The system exhibited impressive **temporal stability**, low latency, and adaptability to various facial structures and lighting conditions.

The absence of a GUI not only streamlined resource usage but also emphasized the model's suitability for integration into **background applications**, **emotion-aware surveillance**, and **human-computer interaction (HCI)** systems.



In comparison to traditional machine learning models, the proposed system provided superior accuracy and generalization, largely due to its ability to extract spatial and structural cues through morphological preprocessing. Visualization tools like saliency and activation maps provided further insight into the decision-making process of the CNN, reinforcing the interpretability of results.

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[13] "Deep Learning Framework for Compound Facial Emotion Recognition" (2023) – This study implements deep learning frameworks for recognizing compound facial emotions using the CFEE dataset. It highlights the advantages of visual-based emotion recognition over sensor-based approaches

[14] "Feature-Based Dual Visual Feature Extraction Model for Compound Multimodal Emotion Recognition" (2025) – This paper presents a multimodal emotion recognition method that fuses Vision Transformer (ViT) and Residual Network (ResNet) features. It was developed for the Affective Behavior Analysis in-the-wild (ABAW) competition and tested on C-EXPR-DB and MELD datasets.

[15]"Feature-Based Dual Visual Feature Extraction Model for Compound Multimodal Emotion Recognition" (2025) – This paper presents a multimodal emotion recognition method that fuses Vision Transformer (ViT) and Residual Network (ResNet) features. You can find it here, Feature-Based Dual Visual Feature Extraction Model for Compound Multimodal Emotion Recognition