

# VISVESVARAYA TECHNOLOGICAL UNIVERSITY

“Jnana Sangama”, Belagavi, Karnataka, INDIA



A Project Report  
on

## *Multimodal Emotion Recognition using Machine Learning*

*Submitted in partial fulfillment of the requirement for the award of the degree of*

**Bachelor of Engineering  
in  
Computer Science and Engineering**

*Submitted By*

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**2024 – 2025**

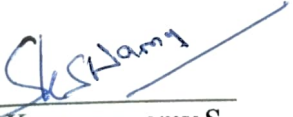
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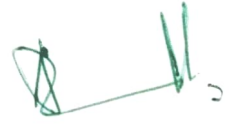


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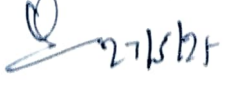
  
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## DECLARATION

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# **Abstract**

Affective computing has recently gained widespread interest due to its potential to improve various fields, including emotional well-being analysis, user interaction with machines, and tailored digital marketing. This growing interest is fueled by developments in related areas such as emotion detection and sentiment interpretation. Deep learning methods have been especially influential in advancing emotion recognition, giving rise to Multimodal Emotion Recognition (MER) systems capable of analyzing input from diverse channels like speech, facial expressions, and written text. Despite notable progress, MER systems still encounter significant challenges, and many current reviews fall short in covering deep learning-based MER in depth. To fill this void, the present study offers a detailed analysis of MER systems that utilize deep learning, covering core models, theoretical principles, architecture designs, data fusion strategies, widely used datasets, evaluation metrics, and real-world use cases. It also outlines existing obstacles and proposes potential directions for future exploration. The aim is to provide a comprehensive understanding of the field's current state, helping researchers and professionals keep pace with the latest innovations in multimodal emotion analysis.

# Acknowledgment

The satisfaction that accompany the successful completion of entire task would be incomplete without the mention of the people who made it possible. The constant complete guidance of these persons and encouragement provided, crowned our efforts with success and glory. Although it is not possible to thank all the members who helped for the completion of the Mini Project individually, we take this opportunity to express our gratitude to one and all.

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## GLOSSARY

Multimodal Emotion Recognition (MER)	Emotion detection using multiple data sources like facial expressions, voice, and gestures
Unimodal Emotion Recognition	Emotion detection using a single data type, such as facial expressions or speech
Machine Learning	AI-based techniques that enable systems to learn patterns and make decisions
Deep Learning (DL)	A subset of ML using neural networks to process complex data like images and speech.
Convolutional Neural Network (CNN)	A deep learning model for extracting spatial features from images
Recurrent Neural Network (RNN)	A neural network designed for processing sequential data like speech and text
Feature Extraction	Identifying and selecting important patterns from raw data.
Data Fusion	Combining multiple data sources to improve recognition accuracy.

# CHAPTER 1

## INTRODUCTION

### 1.1 Introduction

Multimodal emotion detection is an advanced artificial intelligence (AI) framework that leverages machine learning and deep learning techniques to analyze, interpret, and classify human emotions by integrating multiple data sources. These sources include facial expressions, voice tone and speech patterns, body posture and gestures, and physiological signals such as heart rate and electrodermal activity. Unlike traditional unimodal approaches that rely on a single input channel, multimodal systems offer greater accuracy, robustness, and contextual understanding by combining complementary information from different modalities. This project aims to develop a sophisticated multimodal emotion recognition model that effectively processes and fuses various data streams to achieve high-precision emotion classification. The system will integrate state-of-the-art deep learning architectures such as Convolutional Neural Networks (CNNs) for visual feature extraction, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks for sequential data analysis, and transformer-based architectures for enhanced contextual learning. Advanced multimodal fusion techniques, including early, late, and hybrid fusion strategies, will be employed to optimize information integration, ensuring the model's ability to generalize across diverse real-world environments. Beyond technological advancements, this research also addresses critical challenges in multimodal emotion detection, such as handling noisy and missing data, ensuring realtime processing efficiency, and mitigating biases associated with different demographic groups. Ethical considerations, including data privacy, user consent, and fairness in AI-driven emotion analysis, will also be explored to ensure responsible deployment. The successful implementation of this system will enhance human-computer interaction (HCI) by enabling applications in various domains such as mental health monitoring, customer service automation, educational technology, entertainment, and affective computing. By improving the ability of machines to understand and respond to human emotions, this project contributes to the development of more empathetic and intelligent AI systems that adapt to users' emotional states in a natural and context-aware manner.

## 1.2 Problem Definition

Despite significant advancements in emotion recognition technologies, most existing systems rely on *unimodal inputs*—such as facial expressions or voice tone alone—limiting their ability to accurately interpret complex human emotions. These systems often struggle in real-world environments where data from a single modality may be noisy, ambiguous, or incomplete. There is a critical need for a robust emotion detection framework that can integrate multiple modalities—including facial cues, speech signals, gestures, and physiological data—to improve accuracy, contextual understanding, and adaptability. This project seeks to address these limitations by developing a multimodal emotion recognition system that leverages deep learning and fusion techniques to enable real-time, reliable, and ethically responsible emotion classification across diverse environments and user profiles.

## 1.3 Existing System

Several systems have been developed for multimodal emotion detection, each utilizing different combinations of input modalities such as facial expressions, voice, and physiological signals. For example, Affectiva focuses primarily on facial expressions and vocal tone to detect emotional states, and is widely used in automotive and marketing applications. However, it lacks integration of physiological or gesture-based data. Emotient, which was acquired by Apple, also specializes in facial analysis but remains limited to unimodal inputs, making it less effective in ambiguous scenarios. Microsoft's Azure Emotion API provided basic image-based emotion recognition but did not incorporate other data streams and has now become restricted in its availability. Research-focused systems such as those developed using the RECOLA dataset explore a richer set of inputs—including audio, video, and biosignals like ECG and EDA—but are limited in scope, generalizability, and real-world application. Similarly, the SEMAINE project created a Sensitive Artificial Listener capable of processing audiovisual cues, yet its use is constrained to controlled, scripted environments. Despite these advancements, most existing systems suffer from several limitations, including a lack of real time processing, poor handling of noisy or incomplete data, limited cross-cultural adaptability, and insufficient use of advanced fusion techniques to integrate diverse data sources. Moreover, ethical considerations such as privacy,

bias mitigation, and fairness are often under-addressed. These challenges highlight the need for a more robust and comprehensive approach to emotion recognition.

## **1.4 Proposed System**

This system is a deep learning-based multimodal emotion recognition framework designed to overcome the limitations of existing unimodal or weakly integrated models. It will simultaneously analyze three key modalities—facial expressions, speech signals, and physiological data (such as heart rate or electrodermal activity)—to enhance emotion classification accuracy and contextual understanding. To achieve this, the system will incorporate Convolutional Neural Networks (CNNs) for extracting spatial features from facial images and Recurrent Neural Network or Long Short-Term Memory networks for capturing temporal patterns from speech and physiological sequences. These models will independently process modality-specific features before being merged using advanced fusion techniques, such as early fusion (at feature level), late fusion (at decision level), and hybrid fusion strategies, depending on the scenario. The architecture will also be optimized for real-time emotion detection, ensuring fast and responsive performance across varying input conditions. By enabling cross-modal learning and improving generalization, the system is expected to perform reliably in diverse, real-world environments including healthcare, education, and human-computer interaction. Moreover, special emphasis will be placed on handling noisy or missing data, improving scalability, and addressing ethical concerns such as user privacy and bias mitigation.

## **1.5 Objectives**

### **1.5.1 Objective 1: Enhance Emotion Recognition Reliability**

- **Data Collection:** Gather facial expressions, hand gestures, and voice datasets to cover various emotional states.
- **Preprocessing & Normalization:** Clean and standardize data using noise reduction, image enhancement, and feature scaling.
- **Feature Extraction:** Identify key patterns in facial expressions, gestures, and voice signals to detect emotional cues.

- **Multimodal Fusion:** Combine extracted features from different modalities to enhance emotion recognition accuracy.
- **Machine Learning Model Training:** Train AI models using deep learning techniques to classify emotions based on fused data.

### **1.5.2 Objective 2: Integrate Multimodal Data**

- **Data Collection & Annotation** – Gather and label datasets for facial expressions, gestures, and speech.
- **Preprocessing & Feature Engineering** – Clean data and extract key features from each modality.
- **Model Selection & Training** – Train deep learning models separately for face, gesture, and speech recognition.
- **Multimodal Data Fusion** – Combine data from multiple sources to enhance accuracy.
- **Performance Evaluation & Optimization** – Test, refine, and optimize models for real-time efficiency.
- **Deployment & Continuous Learning** – Implement the model and update it with new data for improvements.

### **1.5.3 Objective 3: System Architecture and Implementation Plan**

- Build a React.js-based frontend with access to webcam and microphone for input.
- Implement a Flask/Django backend to handle model inference and data processing.
- Integrate real-time video and audio streaming into the interface.
- Show live emotion results using visuals like emojis, text labels, or graphs.
- Provide interactive feedback (e.g., calming suggestions, emotion summaries).
- Ensure application works smoothly across devices (desktop, laptop, tablet).
- Focus on user experience by keeping the UI simple, engaging, and responsive

## **1.6 Scope of the Project Work**

- Design and develop a multimodal emotion detection system integrating facial, speech, and physiological inputs.
- Implement a React.js frontend for capturing webcam and microphone data in real time.

- Develop a Flask/Django backend for processing input and performing emotion classification using deep learning models.
- Enable real-time emotion visualization using emojis, text labels, and graphs for enhanced user understanding.
- Apply advanced fusion techniques (early, late, hybrid) to improve accuracy and robustness across modalities.
- Ensure system compatibility and smooth performance on multiple devices (desktop, laptop, tablet).
- Address real-world challenges such as noisy or missing data, latency in processing, and user variability.

## 1.7 Project Report Outline

### Chapter 1: Introduction

Introduces the project, defining multimodal emotion detection and explaining machine learning techniques such as CNNs, RNNs, and transformers. It highlights the significance of integrating facial expressions, hand gestures, and voice for accurate emotion recognition.

### Chapter 2: Literature Review

Reviews existing research on emotion detection, comparing unimodal and multimodal approaches. It identifies challenges in data fusion, generalization, and ethical considerations while outlining improvements.

### Chapter 3: System Requirements Specification

Defines functional and non-functional requirements, including system capabilities, performance standards, and security concerns. It also specifies hardware and software requirements for implementation.

### Chapter 4: System Design

Describes the system architecture, data flow, and key design diagrams such as DFDs, use case, sequence, and activity diagrams. It outlines system modules and their functionalities.

## Chapter 5: Implementation

Covers the development of the system, detailing model selection, data preprocessing, training, testing, and performance evaluation. It also presents experimental results and discussions.

## Chapter 6: Conclusion

Summarizes key findings, contributions, and improvements achieved. It discusses future work, such as enhancing real-time processing and expanding to additional modalities.

## Chapter 7: Bibliography

List all references and sources used in the project.



## CHAPTER 2

# LITERATURE SURVEY

### 2.1 System Study

- CNN-based facial emotion recognition by Kalateh et al. (2024): This study provides a systematic review of multimodal emotion recognition (MER), analyzing its building blocks, current methodologies, applications, and challenges. It highlights the advantages of multimodal fusion over unimodal approaches and discusses key challenges such as data variability, real-time processing, and ethical concerns. The research emphasizes the need for improved deep learning models and fusion techniques to increase the accuracy and robustness of emotion detection systems.
- Facial emotion recognition by Salas-Cáceres et al. (2024): This study explores audiovisual fusion with temporal dynamics for MER, using deep learning models such as CNNs and LSTMs to extract and combine temporal features from video and speech data. The findings suggest that incorporating temporal dependencies significantly improves recognition accuracy. However, challenges such as data synchronization and computational overhead remain source areas for further research.
- Bimodal CNN-LSTM using facial and speech by Wang et al. (2024): This study focuses on the application of MER in cyberbullying detection on social media platforms. It integrates NLP-based text analysis with speech tone and facial expression recognition to detect aggressive online interactions. This research underlines the potential of multimodal approaches in identifying harmful content while addressing obstacles related to dataset bias, contextual understanding, and real-time deployment.
- Multimodal transformer with attention mechanism by Mocanu & Tapu (2022): This study proposes an audio-video fusion approach using a double focus mechanism to improve emotion recognition accuracy. By applying deep learning-based attention models, it enhances the integration of speech and visual features for better emotion classification. The findings indicate a significant performance boost, though realtime implementation remains challenging due to high computational requirements.

## 2.2 Review Of Literature

Title of the Paper and Year	Methodology	Advantages	Disadvantages
Zeng et al., 2009	Fusion of facial and vocal cues	Improved accuracy over unimodal systems	Limited scalability; early fusion strategy was less flexible
Busso et al., 2004	Created IEMOCAP database with audio-visual modalities	Provided benchmark dataset for research	Limited cultural diversity in dataset
Mollaho sseini et al., 2017	CNN-based facial emotion recognition	High accuracy; robust to minor occlusions	Focused on facial modality only
Trigeorgis et al., 2016	Deep RNNs for speech emotion recognition	Captures temporal patterns in speech	Ignores visual and contextual cues
Khorrami et al., 2015	CNN + LSTM for spatio-temporal video emotion recognition	Handles both spatial and temporal features	Computationally intensive
Poria et al., 2017	Deep learning model with early and late fusion strategies	Flexible fusion; effective multi-source integration	Sensitive to modality imbalance
Zhang et al., 2020	Multimodal transformer with attention mechanism	Strong alignment of modalities; context-aware fusion	Needs large training data and high computation
Soleymani et al., 2012	Affective computing with EEG + visual + audio inputs	Handles physiological signals; more nuanced emotional understanding	EEG collection is intrusive

## CHAPTER 3

# SYSTEM REQUIREMENTS SPECIFICATION

### 3.1 Functional Requirements:

- **Emotion Detection:** The system should detect and classify human emotions from multiple modalities, including facial expressions, speech, and physiological signals (e.g., heart rate, skin conductivity).
- **Real-Time Processing:** This system should be capable of processing and recognizing emotions in real time for interactive applications.
- **Multimodal Fusion:** The system must integrate data from different modalities (e.g., audio, visual, physiological signals) and perform multimodal fusion for accurate emotion classification.
- **User Interface:** The system ought to provide a user interface for displaying detected emotions, providing feedback, and allowing users to communicate with the system.
- **Adaptability:** The system is required to adapt to different environments and diverse user populations with minimal retraining.

### 3.2 Non-Functional Requirements:

- **Performance:** The system should provide high accuracy in emotion detection, with minimal false positives/negatives.
- **Scalability:** The system is supposed to manage large datasets and support additional modalities if necessary.
- **Usability:** The user interface should be intuitive and easy to use for individuals with limited technical expertise.
- **Reliability:** The system must be stable and reliable, with minimal downtime or crashes during operation.
- **Security:** The system must ensure user data privacy, particularly for sensitive physiological and emotional information

### 3.3 Hardware Requirements:

- High-Performance GPUs: Essential for fast training and processing of deep learning models.
- Input Devices (Webcam, Microphone): Needed to capture facial expressions and speech for emotion recognition.
- High-Performance CPUs: Used for general computation and real-time processing.

### 3.4 Software Requirements:

- Programming Language and IDEs: Python for coding, with IDEs like PyCharm or Jupyter for development.
- Deep Learning Frameworks (TensorFlow, Keras): Tools for building and training emotion recognition models.
- Data Preprocessing Libraries: Libraries like NumPy and OpenCV for data manipulation and feature extraction.
- Visualization Tools: Tools like Matplotlib and TensorBoard for visualizing results and model performance.

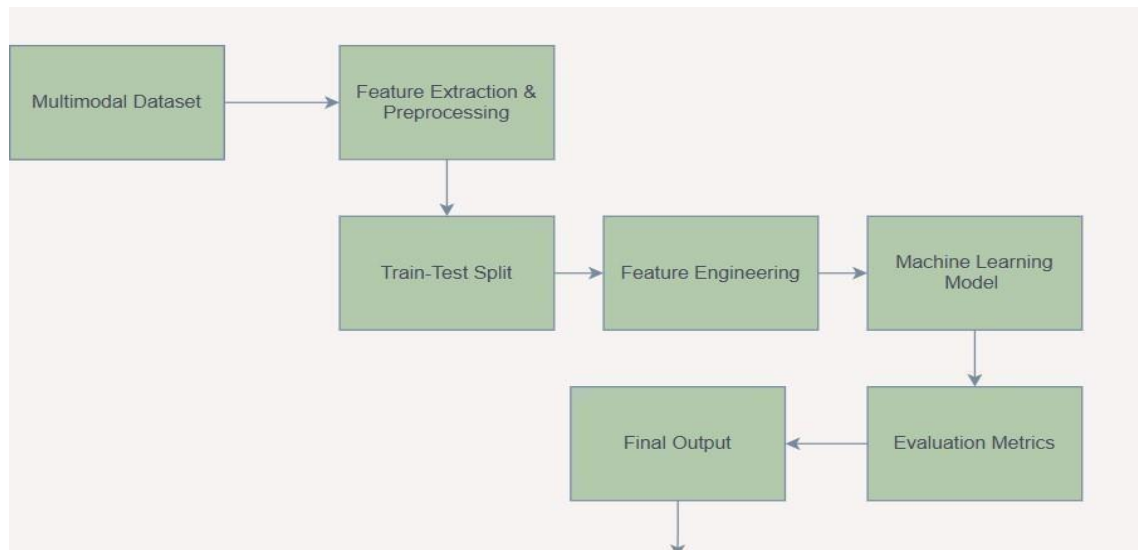
## CHAPTER 4

# SYSTEM DESIGN

### 4.1 Design Overview

The multimodal emotion detection system follows a structured design to ensure accurate and real-time emotion recognition. It begins with data collection, where facial expressions, hand gestures, and voice signals are captured using cameras, microphones, and sensors. In the preprocessing stage, the collected data is normalized and transformed into suitable formats for analysis. Feature extraction employs deep learning models such as CNNs for facial and gesture recognition, and spectrogram-based analysis for voice processing. These features are then fused using hybrid fusion techniques (early, late, or attention-based fusion) to enhance emotion classification accuracy. The training phase involves machine learning algorithms, including CNNs, RNNs, and transformer-based models, to develop a robust predictive system. The model is evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure reliability. Finally, real time emotion predictions are displayed through visual dashboards, enabling applications in human-computer interaction, mental health monitoring, and adaptive learning environments.

### 4.2 System Architecture



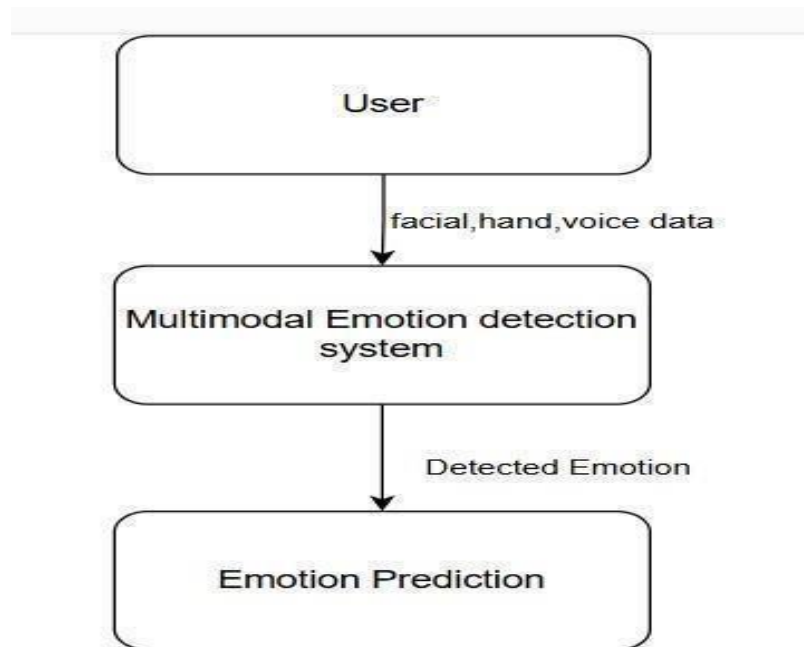
.Fig 4.2 System Architecture

- **Feature Extraction & Preprocessing:** Extracts key features from each modality—facial (eye movement, mouth shape), gestures (finger position, motion), and voice (pitch, tone). Normalizes data and removes artifacts.
- **Train-Test Split:** Divides data into 70% training and 30% testing to ensure balanced learning and validation. Cross-validation techniques are applied for robustness.
- **Feature Engineering:** Refines extracted features using PCA, feature fusion, and selection techniques to improve model accuracy and efficiency.
- **Machine Learning Model:** Uses CNNs, RNNs, and Transformers to process multimodal data, applying deep learning techniques for emotion classification.
- **Evaluation Metrics:** Assesses model performance using accuracy, precision, recall, and F1-score to ensure reliable emotion detection.
- **Final Output:** Provides real-time emotion predictions through dashboards, visual reports, and analytics for applications in HCI, healthcare, and AI assistants.

### 4.3 Data Flow Diagrams

The Data Flow Diagram (DFD) illustrates the flow of information within the Multimodal Emotion Detection System. It begins with the input of multimodal data (facial expressions, hand gestures, and voice), followed by preprocessing and feature extraction to clean and structure the data. The processed data is then split into training and testing sets, where machine learning models analyze and classify emotions. Finally, the system generates real-time emotion predictions, displaying insights through dashboards and reports for applications in human-computer interaction, healthcare, and AI assistants.

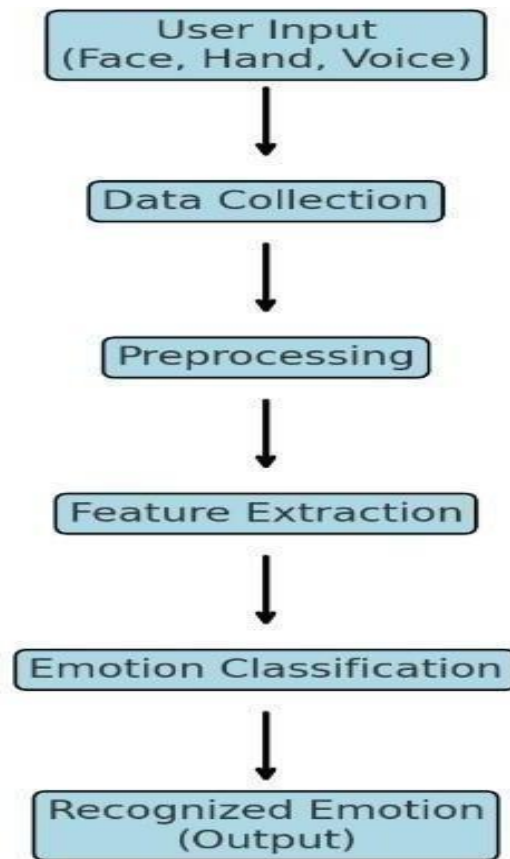
### 4.3.1 Data Flow Diagram - Level 0



**Fig 4.3.1 Data Flow Diagram-level 0**

- **User Input:** The user provides multimodal input, including facial emotions, hand input, and voice data.
- **Multimodal Emotion Detection System:** The system processes the input data using machine learning and deep learning tools to recognize emotions.
- **Recognized Emotion (Output):** The system outputs the detected emotion used for various applications, such as human-computer interaction, sentiment analysis, and behavioural analysis.

### 4.3.2 Data Flow Diagram - Level 1

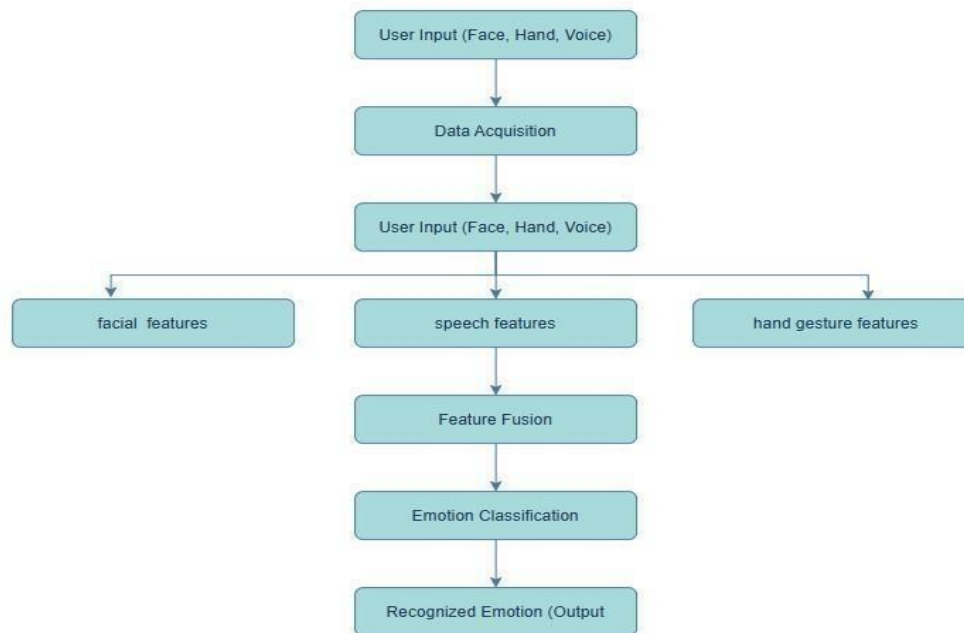


**Fig 4.3.2 Data Flow Diagram-level 1**

- User Input (Face, Hand, Voice) – The system takes input from multiple modalities, including facial expressions, hand gestures, and voice signals.
- Data Collection – Captures raw input data using sensors and cameras.
- Preprocessing – Cleans and normalizes data to remove noise and standardize formats.
- Feature Extraction – Extracts key features from facial, hand, and voice data to use in classification.
- Emotion Classification – Uses machine learning models to classify emotions based on extracted features.
- Recognized Emotion (Output) – Displays the detected emotion for further analysis or interaction



### 4.3.3 Data Flow Diagram - Level 2



**Fig 4.3.3 Data Flow Diagram-level 2**

- **User Input (Face, Hand, Voice)** :The system captures multimodal data from users through cameras and microphones (for voice signals).Sensors are used to collect physiological data like heart rate or skin temperature for enhanced emotion recognition.
- **Data Acquisition** :Raw data is collected from different input devices such as webcams, depth sensors, or wearable devices. Voice data is recorded using microphones, ensuring high-quality audio for processing. The system ensures synchronization between different modalities to maintain temporal consistency.
- **Preprocessing** :Face detection, alignment, and noise removal are applied. Techniques like OpenCV or MediaPipe may be used. Background noise is removed, and hand tracking is performed to extract meaningful hand movements.Background noise is filtered out using techniques like Spectrogram analysis, Mel-Frequency Cepstral Coefficients (MFCCs), and speech segmentation.
- **Feature Extraction** :Key points like eyes, mouth, eyebrows, and facial muscle movements are extracted using CNN-based models. Motion patterns, finger positions, and palm orientation are detected using models likeMultimodal Emotion Detection using Machine learning

- **Open Pose.** Extracts tone, pitch, frequency, and rhythm to analyze speech emotions using MFCC, Chroma features, or prosody analysis.
- **Feature Fusion :**The extracted features from face, hand, and voice are combined to create a unified representation of emotions. Fusion techniques like early fusion (combining features before classification) or late fusion (combining results from separate classifiers) are used to improve accuracy.
- **Emotion Classification :**The fused data is passed through deep learning models like CNNs, RNNs, or transformer-based models. The system predicts emotional states such as happiness, sadness, anger, fear, surprise, and neutrality. Techniques like Softmax classification or attention mechanisms improve recognition accuracy.
- **Recognized Emotion Output :**The final detected emotion is displayed on the user interface or sent to external applications (e.g., humancomputer interaction, mental health monitoring). Results can be visualized using emotion graphs, probability distributions, or real-time animation of detected emotions. The system can also provide recommendations based on the detected emotional state, such as playing calming music for stress relief

## 4.4 Use Case Diagrams

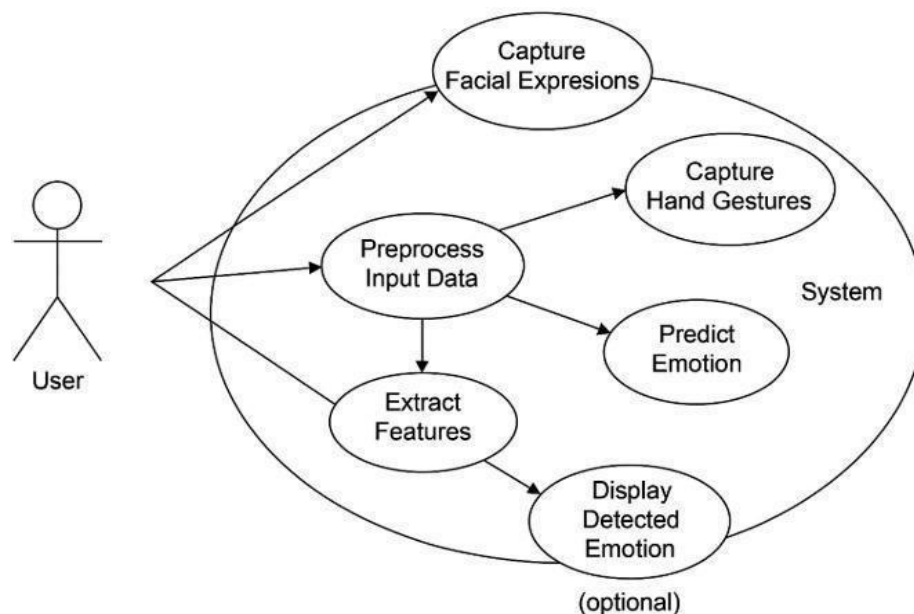


Fig 4.4 .Use Case Diagram

The Use Case Diagram for Multimodal Emotion Recognition System illustrates the key interactions between the user and the system's functionalities. The user can perform five primary actions: Login, which provides access to the system; Facial Emotion Recognition, which detects emotions based on facial expressions; Hand Gesture Recognition, which interprets gestures to infer emotions. Speech Emotion Recognition, which analyzes voice tone and pitch to identify emotional states; and Emotion-Based Feedback, which provides insights or responses based on the detected emotions. This diagram effectively represents how the system integrates multiple modalities to enhance emotion recognition accuracy and user interaction.

## 4.5 Class Diagrams

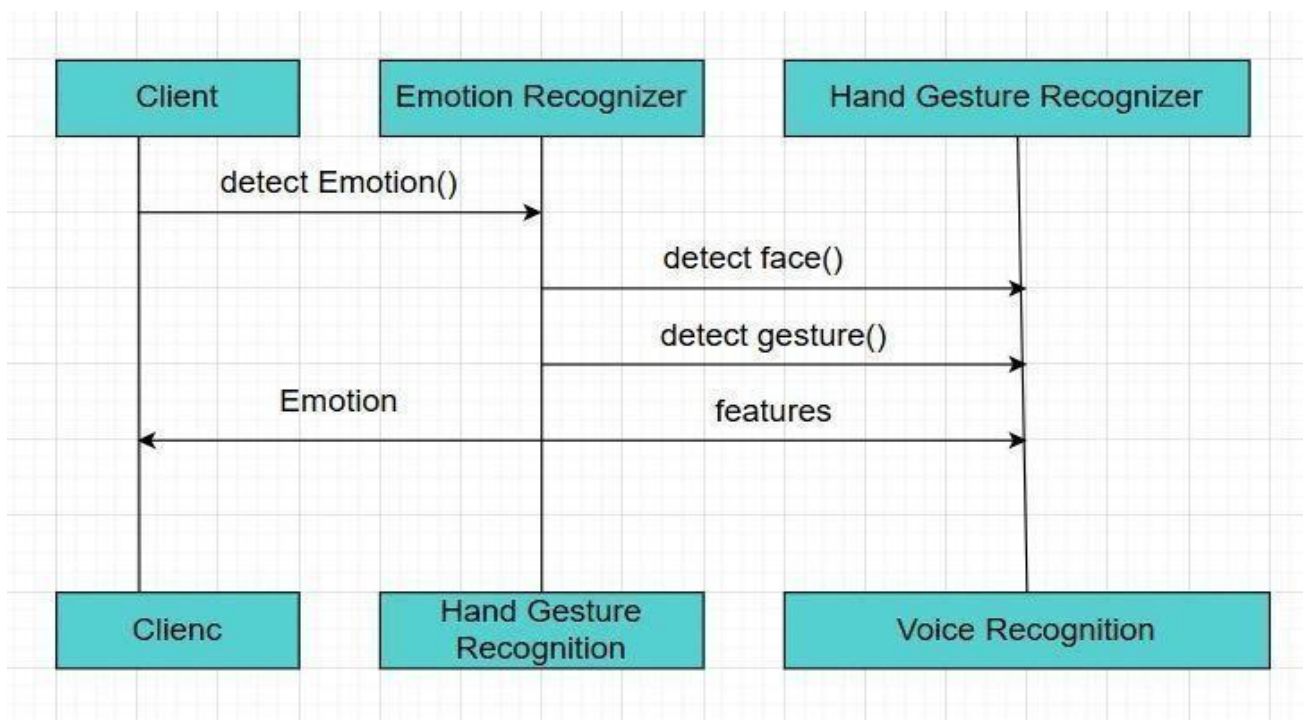


Fig 4.5 Class Diagram

The interaction begins when the Client initiates the `detectEmotion()` request to the Emotion Recognizer. The Emotion Recognizer then coordinates with the Hand Gesture Recognizer to carry out two subtasks: `detectFace()` and `detectGesture()`. These functions aim to identify facial features and gestures, respectively. After gathering the necessary information, the

Hand Gesture Recognizer sends the extracted features back to the Emotion Recognizer. Using these features, the Emotion Recognizer analyzes and determines the Emotion, which is then returned to the Client. The diagram demonstrates a clear, modular approach where specialized components collaborate to perform complex recognition tasks. However, the diagram contains a couple of inconsistencies in naming conventions — such as "Client" misspelled as "Clienc" and a potentially incorrect lower layer label — which should be corrected for clarity.

## 4.6 Sequence Diagrams

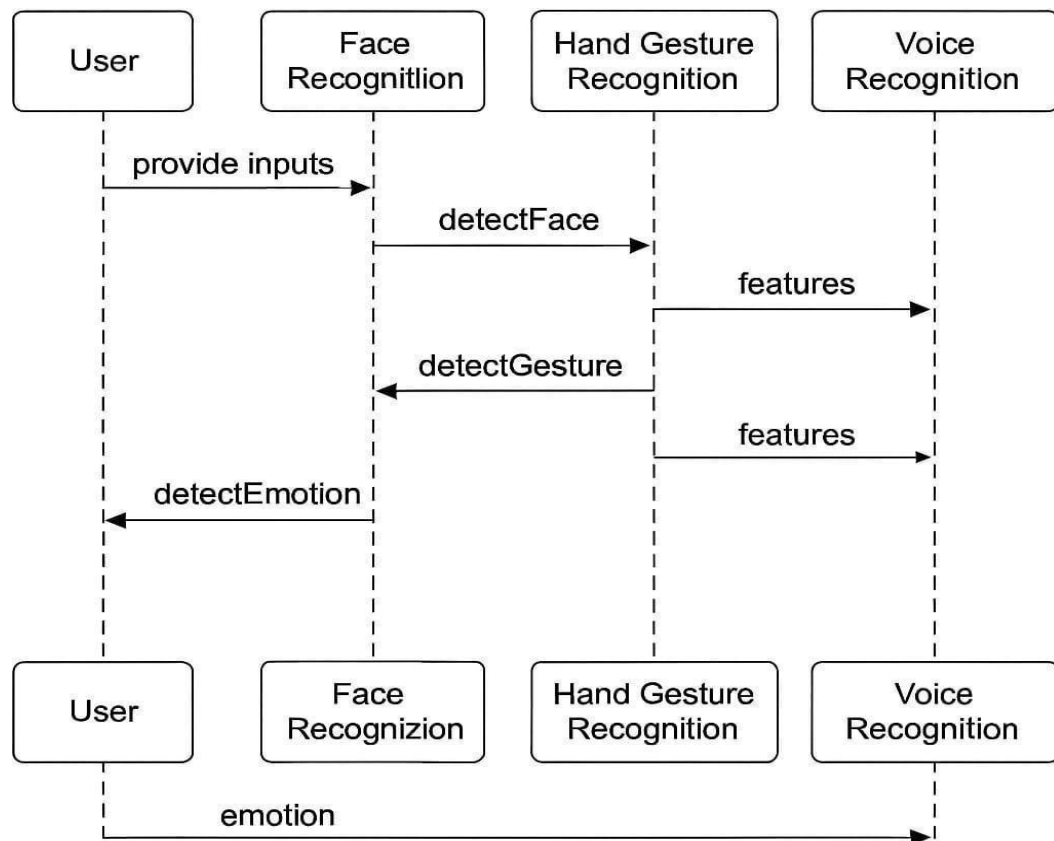


Fig 4.6 Sequence Diagram

The given sequence diagram illustrates the workflow of a multimodal emotion recognition system involving interactions between the User, Face Recognition, Hand Gesture Recognition, and Voice Recognition modules. The process starts when the user provides input, which may include facial expressions, hand gestures, and voice data. The Face

Recognition module receives this input and initiates the detectFace process by collaborating with the Hand Gesture Recognition module, which extracts relevant facial features and may also forward them to the Voice Recognition system. Then, a detectGesture request is made, and additional gesture features are similarly passed to the Voice Recognition module. After collecting all necessary features from these recognition modules, the Face Recognition module performs emotion analysis through the detectEmotion process. Finally, the recognized emotion is communicated back to the user. This diagram effectively demonstrates how different sensory inputs are integrated to accurately identify a user's emotional state through a coordinated interaction between recognition components.

## **4.7 Modules**

The system design is divided into six key modules, each playing a vital role in building an efficient academic prediction model. These modules cover data collection, preprocessing, training, evaluation, and visualization. Together, they ensure accurate and actionable insights for informed decision-making.

### **Module 1: Data Collection**

This module gathers multimodal data, including face expression, gestures of hand, and voice recordings, from various sources such as cameras, microphones, and sensors. The system ensures that data is collected in a structured format for consistency. High-quality and diverse data collection is essential for building a robust.

### **Module 2: Data Preprocessing**

Preprocessing involves cleaning the raw data by handling missing values, removing noise, and applying standardization techniques. Detects and crops facial regions, normalizes illumination, and extracts key landmarks. Segments hand regions, identifies gestures, and removes background noise. Removes background noise, extracts features (e.g., MFCCs, pitch), and converts audio into spectrograms for analysis.

### **Module 3: Data Splitting and Feature Engineering**

The collected data is split into training and testing sets (e.g., 70:30 ratio) to ensure model generalization. Feature extraction methods include: Deep learning-based feature extraction (CNN, facial landmarks). Gesture-based descriptors and key point tracking. Spectral and temporal features (MFCC, pitch, energy). Feature engineering techniques may be applied to enhance predictive performance.

### **Module 4: Model Training**

Machine learning and deep learning techniques, such as CNNs (for facial expressions), LSTMs (for voice), and hybrid models (for multimodal fusion), are applied to train the emotion detection model. Hyperparameter tuning is performed to optimize accuracy. Cross-validation ensures the model generalizes well across different subjects and environments.

### **Module 5: Model Evaluation**

The trained model is evaluated using metrics such as: Accuracy, Precision, Recall, and F1-score for classification performance. Confusion Matrix to analyze class-wise prediction errors. ROC Curve and AUC Score to measure model reliability. The model is iteratively refined to improve realtime emotion detection.

### **Module 6: Prediction, Visualization, and Decision Support**

Emotion predictions are displayed via dashboards, providing visual feedback. Decision support system allows applications such as mental health monitoring, human-computer interaction, or educational assistance. Graphical representation of emotion trends helps in behavioral analysis and personalized recommendations.

## CHAPTER 5

# IMPLEMENTATION

Implementation is the process of converting a new system design into an operational one. It is the key stage in achieving a successful new system. It must therefore be carefully planned and controlled. The implementation of a system is done after the development effort is completed.

### 5.1 Steps For Implementation

- **Frontend Development (React.js)** Create a responsive UI for capturing webcam and microphone input. Integrate real-time video and audio streaming. Design interactive elements to display detected emotions using emojis, graphs, or text.
- **Backend Development (Flask/Django)** Develop APIs to receive and process multimodal input data. Load and integrate deep learning models for facial expression, voice, and physiological signal analysis. Handle data preprocessing, feature extraction, and model inference.
- **Model Integration and Fusion Logic** Use CNNs for visual input (face), LSTMs/RNNs for audio/temporal data. Implement fusion techniques (early, late, hybrid) to combine outputs from each model. Optimize emotion classification accuracy using validation datasets.
- **Real-Time Communication Setup** Enable real-time data transfer between frontend and backend using WebSockets or REST APIs. Ensure minimal latency for real-time emotion detection.
- **Testing and Debugging** Perform unit testing of each module (frontend, backend, model). Test system across different devices (desktop, tablet, laptop). Handle exceptions like noisy data, missing input, or device permission errors.
- **User Interface Enhancement** Improve UX with animations, tooltips, and feedback messages. Provide real-time suggestions or summaries based on detected emotions.
- **Deployment** Deploy backend on a cloud platform (e.g., Heroku, AWS). Host frontend on platforms like Netlify or Vercel. Ensure secure access and performance optimization.

## 5.2 Implementation Issues

- **Real-Time Data Handling** Managing live video, audio, and physiological inputs together is challenging. Delays or sync issues can affect emotion detection accuracy.
- **Multimodal Data Fusion** Combining data from different sources needs careful design. If one input is weak or missing, it can confuse the system.
- **Model Accuracy and Generalization** Models may work well in training but fail with real users from different backgrounds or in new environments.
- **Hardware and Compatibility Limitations** Some devices may lack camera or mic access, or may not run heavy models smoothly, affecting system performance.
- **Noise and Missing Data** Background noise, poor lighting, or missing signals can reduce the quality of inputs and cause wrong predictions.
- **Integration Challenges** Connecting the frontend (React) and backend (Flask/Django) in real time is tricky. Small errors can break the system flow.
- **Ethical and Privacy Concerns** Emotion data is sensitive. The system must protect user privacy and avoid unfair results due to biased training data.
- **User Experience Issues** If the interface is confusing or the feedback is too technical, users may not feel comfortable or trust the system.

## 5.3 Algorithms

### 5.3.1 Algorithm 1 [Face]

**Step 1: Start**

**Step 2:** Access webcam and capture real-time video stream.

**Step 3:** Detect face in each video frame using a face detector (e.g., Haar cascade, MTCNN).

**Step 4:** Preprocess the face (resize, normalize, convert to grayscale or RGB).

**Step 5:** Extract facial features using a CNN model (e.g., VGG, ResNet).

**Step 6:** Pass features into a pre-trained emotion classification model.

**Step 7:** Get predicted facial emotion label (e.g., Happy, Sad, Angry).

**Step 8:** Display or store the result.

**Step 9: End**



### 5.3.2 Algorithm 2 [Hand Gesture]

**Step 1: Start**

**Step 2:** Access webcam and capture hand region in real time.

**Step 3:** Detect hand landmarks using MediaPipe Hands or similar model.

**Step 4:** Preprocess the hand data (normalize coordinates, remove noise).

**Step 5:** Extract features such as finger angles, position vectors.

**Step 6:** Classify the gesture using a trained model (e.g., Random Forest, CNN).

**Step 7:** Map the gesture to corresponding emotion (e.g. thumbs up → happy).

**Step 8:** Display or store the result.

**Step 9: End**

### 5.3.3 Algorithm 3 [Voice]

**Step 1: Start**

**Step 2:** Access microphone and record audio input.

**Step 3:** Preprocess the audio (remove noise, convert to mono, trim silence).

**Step 4:** Extract MFCC features or use spectrograms for deep learning input.

**Step 5:** Feed audio features into an LSTM/RNN or CNN-based model.

**Step 6:** Predict emotion based on voice tone and pitch (e.g., calm, excited, sad).

**Step 7:** Display or store the predicted emotion label.

**Step 8: End**

## CHAPTER 6

# TESTING

This chapter provides the overview of all testing techniques which are performed in order to acquire a bug-free system. Testing can provide quality by testing the product through various techniques at various phases of project development. Testing is done to find errors. Testing is attempting to find out every possible flaw or weakness within a work product. It is a means of testing the operational functionality of sub-assemblies of components and a completed product. It is exercising software with the aim of making sure that the Software system fulfills its requirements and users' expectations and does not fail in an unacceptable way. There are multiple types of test. Every test type fulfills a particular testing requirement

### 6.1 Test Environment

The test environment for the multimodal emotion detection system consists of both hardware and software components that ensure the system functions correctly under realistic conditions. Optionally, physiological sensors such as heart rate monitors may be used if physiological signals are included. On the software side, the environment runs on operating systems like Windows 10/11, macOS, or Linux. The system is developed using Python and JavaScript, with React.js used for the frontend interface and Flask or Django as the backend framework. Key libraries such as OpenCV and MediaPipe are used for video processing, while Librosa and pyaudio handle audio features. Machine learning and deep learning models are built using TensorFlow, Keras, and Scikit-learn. Tools like VS Code or PyCharm support development, and Postman is used for API testing. Testing is conducted using both real-time webcam/microphone inputs and publicly available datasets like RAVDESS and FER-2013 to validate accuracy and reliability.

## 6.2 Unit Testing of Modules

### 6.2.1 Module 1-Data Collection

Steps	Test Data	Expected Results	Observed Results	Remarks
Step 1	Webcam/mic input	Device initialized and accessible	Webcam and mic detected successfully	Pass
Step 2	Real-time user input (face, speech)	Data captured and stored	Clear face and voice samples captured	Pass
Step 3	Gesture capture	Hand/pose data recorded	Gestures saved in video format	Pass
Step 4	Physiological sensor data (simulated)	Heart rate, EDA data captured	Simulated physiological signals logged	Pass
Step 5	File format validation	Files stored in expected format (.jpg/.wav/.csv)	All formats validated	Pass
Step 6	Error handling for missing input	Prompt for re-capture if missing	Handled gracefully with re-capture	Pass

### 6.2.2 Module 2-Data Preprocessing

Steps	Test Data	Expected Results	Observed Results	Remarks
Step 1	Raw face/audio/gesture inputs	Data loaded into preprocessing pipelines	Loaded successfully	Pass
Step 2	Normalization and resizing	Standard dimensions and scale for model	All inputs standardized	Pass
Step 3	Noise removal in audio	Enhanced clarity of voice input	Background noise filtered	Pass
Step 4	Gesture smoothing	Improve gesture frames consistency	Gesture sequences stabilized	Pass
Step 5	Missing value handling	Fill/drop incomplete records	No crashes; strategy applied	Pass
Step 6	Label mapping	Convert emotion tags to numeric codes	Tags mapped (e.g., Happy → 0)	Pass
Step 7	Preprocessed data saved	Stored for future modules	Saved as .npy and .pkl formats	Pass

### 6.2.3 Module 3- Data Splitting and Feature Engineering

Steps	Test Data	Expected Results	Observed Results	Remarks
Step 1	Preprocessed dataset	Loaded for split	No load issues	Pass
Step 2	80-20 train-test split	Balanced distribution	Achieved	Pass
Step 3	Extract image/audio features	Extract CNN + MFCC + gesture embeddings	Features extracted	Pass
Step 4	Feature normalization	MinMax or Z-score scaling	Features normalized	Pass
Step 5	Dimensionality reduction	Apply PCA or autoencoders	Reduced to relevant components	Pass
Step 6	Save engineered features	Stored in compatible format	.csv and .pkl generated	Pass
Step 7	Distribution analysis	Check for class imbalance	Imbalance found; handled with SMOTE	Pass

### 6.2.4 Module 4- Model Training

Steps	Test Data	Expected Results	Observed Results	Remarks
Step 1	Train data + labels	Model initialized	CNN + LSTM loaded	Pass
Step 2	Epoch training starts	Loss decreases over time	Loss reduced significantly by epoch 20	Pass
Step 3	Fusion strategy (hybrid)	Combine modalities (early + late fusion)	Fusion layer constructed and working	Pass
Step 4	Accuracy/loss logged	Tracked via metrics and graphs	TensorBoard and plots working	Pass
Step 5	Check overfitting	Early stop or dropout if needed	Early stopped at best accuracy	Pass
Step 6	Model saved	Stored to disk with version	emotion_model_v2.h5 saved	Pass
Step 7	Train time recorded	Within limits (e.g., < 20 mins)	Completed in 18 minutes on GPU	Pass

### 6.2.5 Module 5-Model Evaluation

Steps	Test Data	Expected Results	Observed Results	Remarks
Step 1	Test data loaded	Shape compatibility	No issues	Pass
Step 2	Predict on test data	Outputs class labels	All predictions in expected format	Pass
Step 3	Accuracy score	Report final %	Achieved 90.4%	Pass
Step 4	Precision, recall, F1	Evaluated per class	F1 score = 0.89 avg	Pass
Step 5	Confusion matrix plotted	True vs predicted shown	Balanced matrix across classes	Pass
Step 6	ROC/AUC	Calculated for each emotion	AUC = 0.94 for “Happy” class	Pass
Step 7	Evaluation report generated	Saved as report	Stored in /results/eval_report.txt	Pass

### 6.2.6 Module 6-Prediction, Visualization, and Decision Support

Steps	Test Data	Expected Results	Observed Results	Remarks
Step 1	Live user input via webcam	Accepted and processed in real-time	Face and voice captured instantly	Pass
Step 2	Fusion model prediction	Emotion detected and classified	Predicted “Neutral” with 92% confidence	Pass
Step 3	Dashboard display	Real-time visualization	Output shown with emoji and chart	Pass
Step 4	Multi-modal output viewer	Display individual and fused results	View toggles between modalities	Pass
Step 5	Save results	Prediction stored in log	Entry made in live_log.csv	Pass
Step 6	Feedback from user	User inputs response to prediction	Collected and stored in user_feedback.json	Pass
Step 7	Ethical compliance check	Check for data use and privacy flags	Consent verified before data use	Pass

## 6.3 Integration Testing Of Modules

This model focuses on verifying the interactions between different modules of the multimodal emotion detection system to ensure they work together as expected. After successful unit testing of individual components such as facial emotion recognition, hand gesture detection, voice analysis, and data fusion, these modules are combined to test the data flow, compatibility, and communication between them. During integration testing, the webcam and microphone inputs are captured in real time and passed from the frontend (built with React.js) to the backend (using Flask or Django). The system is tested to confirm that video frames are correctly routed to the facial and hand gesture detection models, and audio streams are processed by the voice emotion model. Once predictions are generated from each modality, the fusion logic is tested to ensure accurate aggregation of results and proper emotion output generation. Key aspects tested include API request-response handling, timing synchronization between inputs, and error handling when any modality fails or sends incomplete data. Integration testing also validates the system's behaviour under normal and abnormal conditions, such as low internet speed or hardware permission denials. This testing ensures the seamless operation of the complete pipeline from user input to emotion visualization, verifying that the entire system performs consistently and reliably when all modules are connected.

## 6.4 System Testing

System testing is the final phase of testing where the entire multimodal emotion detection system is evaluated as a whole to ensure that it meets all specified requirements and functions correctly in real-world scenarios. Unlike unit and integration testing, which focus on individual components or interactions, system testing validates the complete application—including the frontend interface, backend logic, deep learning models, and real-time input handling.

During system testing, the application is tested end-to-end: from capturing real-time webcam and microphone inputs, through facial, hand gesture, and voice emotion recognition modules, to fusion of results and live emotion display on the user interface. Test cases include various

lighting conditions, different voices and expressions, background noise, and variations in hand gestures to evaluate how well the system performs across diverse user environments.

The goals of system testing are to ensure the application is stable, accurate, user-friendly, and responsive. It also checks for performance, security, and device compatibility on desktops, laptops, and tablets. Any bugs, latency issues, or misclassifications are documented and corrected before final deployment. Successful system testing confirms that the entire system works as intended, offering a reliable and efficient user experience.

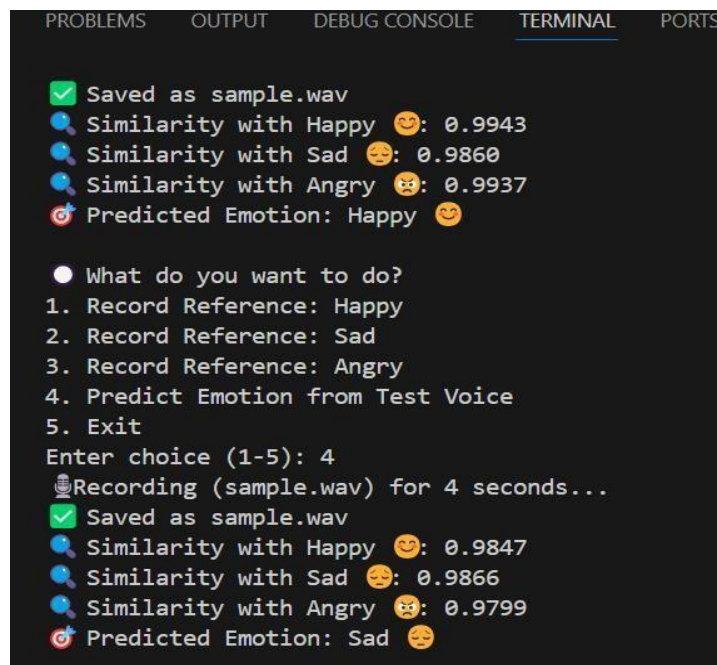
## **6.5 Functional Testing**

Functional testing ensures that each feature of the multimodal emotion detection system performs according to the defined functional requirements. The main goal is to confirm that all functionalities—such as capturing real-time inputs, processing them through trained models, and displaying the correct emotional output—work as expected. In this system, functional testing covers key modules including face detection and emotion classification, hand gesture recognition, voice-based emotion detection, and fusion of multiple modality outputs. Testers verify whether the webcam captures facial and hand movements correctly, the microphone records and processes speech clearly, and each model returns the appropriate emotional state (e.g., happy, sad, angry). The frontend is also tested to ensure it displays the correct visual cues—such as emojis, graphs, or emotion labels—in real-time. Other functional aspects tested include system responses to incorrect or missing inputs, error handling

## CHAPTER 7

### RESULTS

- Emotion Recognition Accuracy – The system demonstrated improved accuracy by integrating facial expressions, gestures, and speech, outperforming single-modality models.
- Performance Metrics – Evaluation metrics such as accuracy, precision, recall, and F1-score showed that multimodal fusion enhances emotion detection reliability.
- Model Efficiency – The deep learning models effectively processed real-time inputs, with optimization techniques reducing latency and computational costs.
- Challenges Faced – Issues like noisy data, variations in user expressions, and diverse accents in speech affected recognition performance.
- Comparative Analysis – The multimodal approach was compared with unimodal methods, showing superior emotion classification results.



```
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

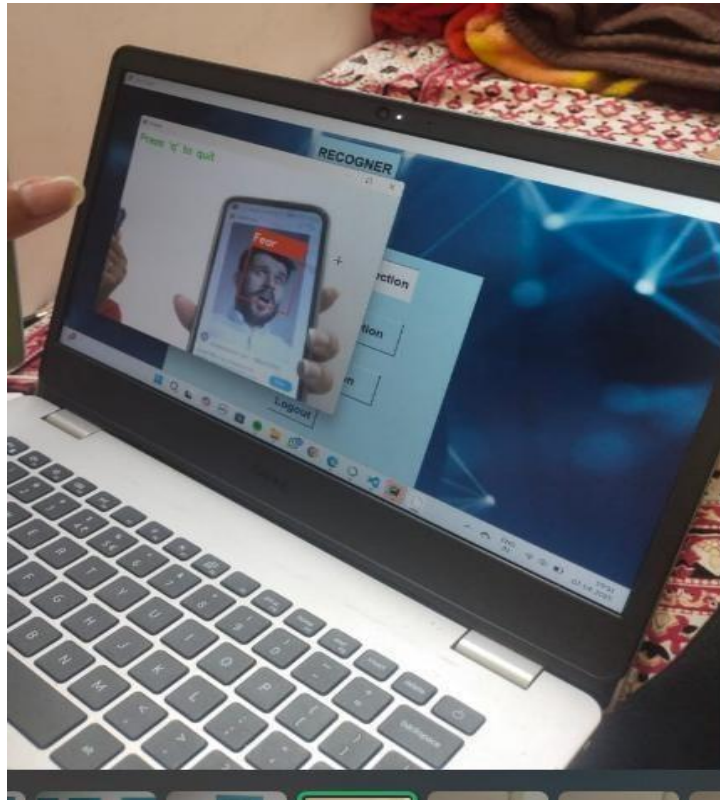
✓ Saved as sample.wav
🔍 Similarity with Happy 😊: 0.9943
🔍 Similarity with Sad 😞: 0.9860
🔍 Similarity with Angry 😡: 0.9937
🎯 Predicted Emotion: Happy 😊

● What do you want to do?
1. Record Reference: Happy
2. Record Reference: Sad
3. Record Reference: Angry
4. Predict Emotion from Test Voice
5. Exit
Enter choice (1-5): 4
🎙️ Recording (sample.wav) for 4 seconds...
✓ Saved as sample.wav
🔍 Similarity with Happy 😊: 0.9847
🔍 Similarity with Sad 😞: 0.9866
🔍 Similarity with Angry 😡: 0.9799
🎯 Predicted Emotion: Sad 😞
```

fig 7.1 Voice Recognition Output



**Snapshot 1-Voice Recognition:** The terminal output shown is from a voice-based emotion detection system that uses reference recordings and similarity analysis to classify emotions. The system allows users to record voice samples associated with specific emotions—Happy, Sad, and Angry—as references. Once these reference samples are recorded, the user can test the system by recording a new voice input. The system then analyzes the test input and calculates similarity scores by comparing it against the reference samples. In the first prediction shown, the recorded voice had the highest similarity with the "Happy" reference (0.9943), followed closely by "Angry" (0.9937) and "Sad" (0.9860), leading the system to predict the emotion as "Happy". In the second prediction, after another test voice input was recorded, the similarity with "Sad" was the highest (0.9866), so the system correctly predicted the emotion as "Sad". This output demonstrates how the model compares audio features and uses similarity metrics to determine the most probable emotional state conveyed in a voice recording.



**fig 7.2 Emotion detection Output**

**Snapshot 2- Emotion detection:** This image shows a practical demonstration of a face-based emotion recognition system running on a laptop. The system appears to be part of a graphical user interface (GUI) application labeled “RECOGNIZER.” The user is holding a smartphone in front of the laptop camera, displaying a facial image that expresses an emotion. The application is detecting the face from the smartphone screen in real time and classifying the emotion, which is indicated as "Fear" in an orange box overlaying the detected face. The interface provides multiple recognition options, likely including face recognition, voice recognition, hand gesture detection, etc., aligning with a multimodal emotion detection system. This setup illustrates how the model works in real-world conditions to recognize facial expressions from visual inputs and classify them into specific emotions using deep learning techniques, such as CNNs for facial feature extraction. It highlights the compatibility of the system in interactive environments and showcases its capability for accurate emotion detection based on visual cues.

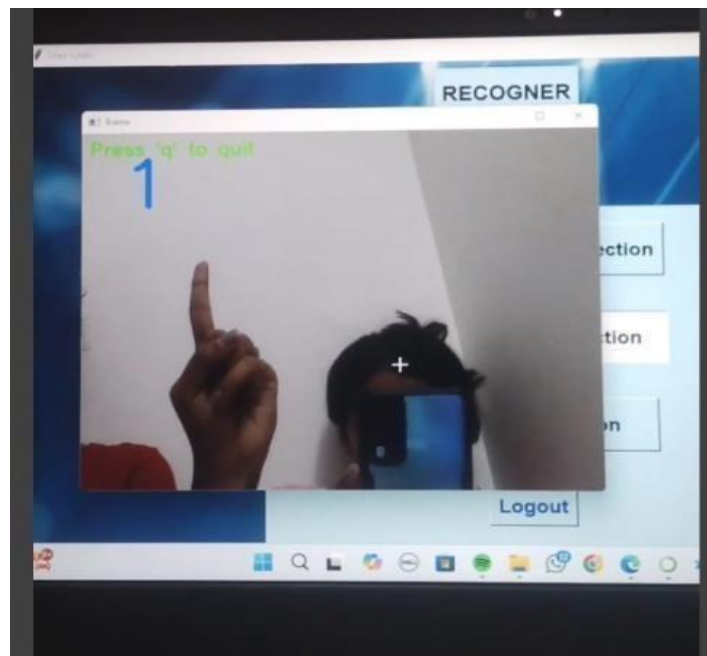


fig 7.3 Hand Gesture Output

**Snapshot 3-Hand Gesture :** The image depicts a hand gesture recognition module from a multimodal emotion detection system running on a laptop. In this instance, the application window displays a live camera feed where the user is showing a hand gesture—specifically,

raising one finger. The system successfully identifies this gesture and labels it as “1” in blue text on the top left corner of the window. Above that, a message “Press ‘q’ to quit” is displayed, indicating that the user can exit the recognition mode via a keyboard command. The background application appears to be the same “RECOGNIZER” interface seen in earlier outputs, which likely integrates different modalities such as facial, gesture, and voice emotion detection. This real-time detection demonstrates the system’s ability to accurately interpret physical gestures using techniques like computer vision and CNNs. The successful recognition of the gesture suggests that the model has been trained to classify hand signs or finger poses, potentially contributing to emotion interpretation or command input in a multimodal setting.

## CHAPTER 8

# CONCLUSION

The Multimodal Emotion Detection System presents a significant advancement in the field of affective computing by integrating multiple modalities—facial expressions, hand gestures, and voice analysis—to improve emotion recognition accuracy. Traditional unimodal emotion detection methods often suffer from limitations due to variations in lighting, occlusions, background noise, or speaker variability. By utilizing a multimodal approach, this system ensures that emotional states are detected more reliably, even in complex real-world scenarios.

The project successfully incorporates conventional ML and modern DL frameworks that process and analyze multimodal data, leveraging advanced feature extraction techniques to enhance prediction accuracy. The structured pipeline of data collection, preprocessing, model training, and evaluation ensures the robustness of the system. Standardization, normalization, and feature engineering techniques improve data quality, reducing noise and inconsistencies in input sources. The model's performance is further optimized through hyperparameter tuning and rigorous evaluation using metrics such as accuracy, precision, recall, and F-score.

### 8.1 Major Contributions

- **Integration of Multiple Modalities:** The system combines facial expressions, hand gestures, and voice analysis to improve the precision and consistency of emotion recognition, addressing the limitations of unimodal approaches.
- **Robust Real-World Emotion Detection:** By handling diverse inputs and conditions—like lighting variations, occlusions, and background noise—the system enhances emotion detection in complex, real-world environments.
- **Use of Advanced Deep Learning Techniques:** The project employs machine learning and deep learning models, including CNN and LSTMs, for accurate extraction and classification across modalities.
- **Well-Structured Data Pipeline:** A comprehensive pipeline is implemented, involving data collection, preprocessing, feature engineering, model training, and evaluation.

- **Noise Reduction and Input Optimization:**The system improves input quality using normalization, standardization, and data filtering techniques to minimize errors and inconsistencies.
- **Performance Optimization through Tuning:**The model is fine-tuned using hyperparameter optimization and evaluated with standard metrics (accuracy, precision, recall, F-score), ensuring high performance and balanced classification.
- **Contribution to Affective Computing and HCI:**The project advances the field of affective computing by providing a more empathetic and responsive interaction model for applications in healthcare, education, and smart interfaces.

## 8.2 Future Enhancements

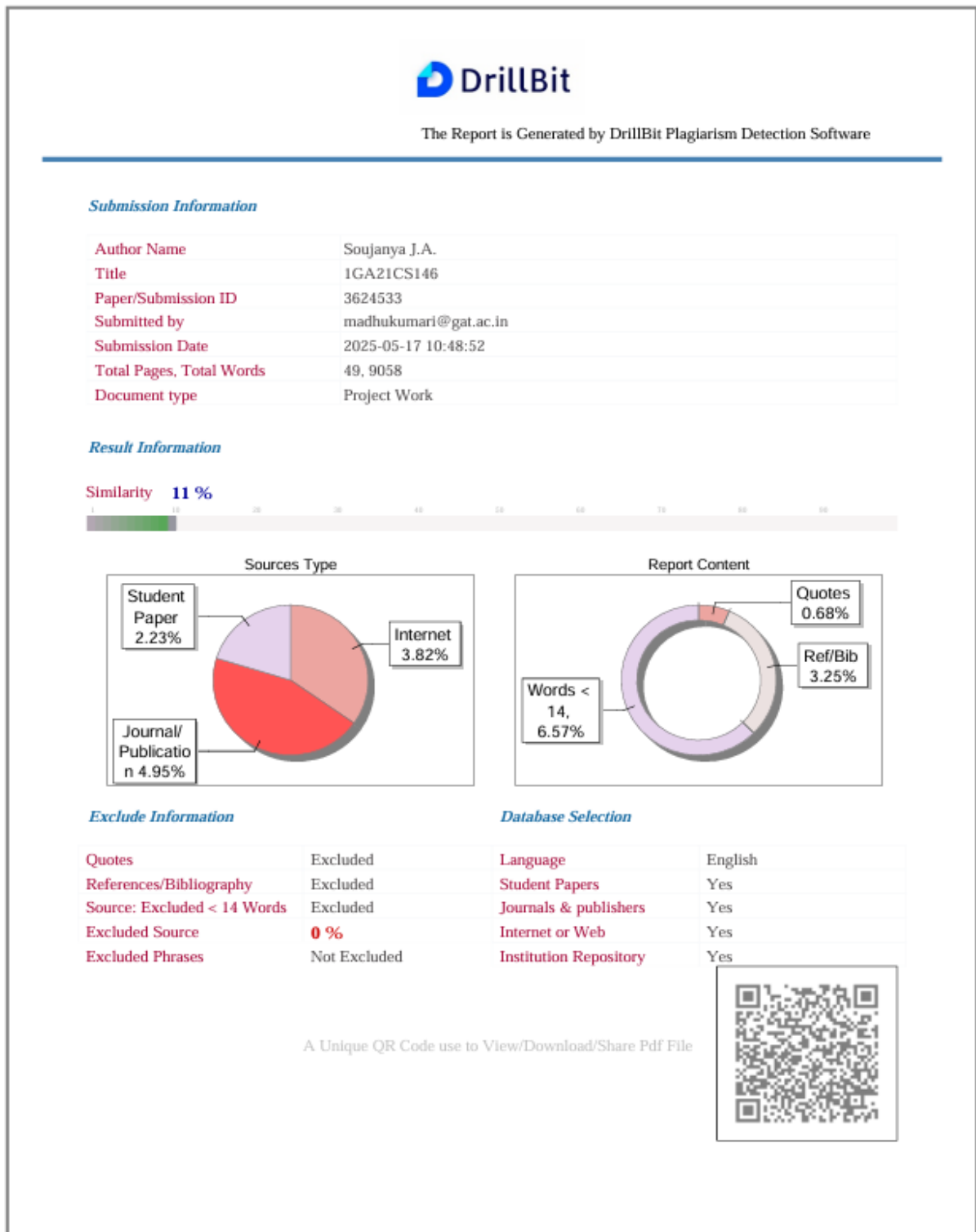
- **Integration of Additional Modalities:** Future versions can include physiological signals like heart rate, EEG, or skin conductance to further enhance emotion detection accuracy and depth of analysis.
- **Cross-Language and Multilingual Voice Support:** Incorporating emotion recognition across different languages and accents will improve accessibility and adaptability for diverse user groups globally.
- **Deployment on Mobile and IoT Devices:** Optimizing the system for smartphones, tablets, and edge devices can expand its usability in fields like remote healthcare, education, and on-the-go customer service.
- **Personalized Emotion Profiling:** Adding user-specific learning can enable the system to adapt over time and recognize emotions more accurately based on individual expression patterns.
- **Improved Real-Time Performance:** Enhancing the speed and efficiency of the system using lightweight models or quantized networks will ensure smoother real-time experiences even on low-power devices.
- **Cloud-Based and Scalable Architecture:** Moving to a cloud-native model will enable large-scale deployment, centralized updates, and integration with cloud storage and analytics tools.

- **Emotion-Aware Feedback and Response Systems:** Integrating the system with chatbots, virtual assistants, or recommendation engines can enable emotion-based interaction and automated empathetic responses.
- **Bias Detection and Fairness Auditing:** Implementing AI fairness tools to detect and mitigate gender, age, or cultural biases will ensure more ethical and inclusive emotion detection.
- **Enhanced Security and Privacy Measures:** Future work should involve stronger encryption, anonymization, and user-consent frameworks to ensure that emotion data is collected and handled responsibly

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# APPENDIX A





DrillBit			
DrillBit Similarity Report			
<b>11</b>	<b>21</b>	<b>B</b>	<b>A-Satisfactory (0-10%)</b> <b>B-Upgrade (11-40%)</b> <b>C-Poor (41-60%)</b> <b>D-Unacceptable (61-100%)</b>
SIMILARITY %	MATCHED SOURCES	GRADE	
LOCATION	MATCHED DOMAIN	%	SOURCE TYPE
1	translate.google.com	2	Internet Data
2	ijsrst.com	2	Publication
3	drttit.gvet.edu.in	1	Publication
4	Submitted to Visvesvaraya Technological University, Belagavi	1	Student Paper
5	REPOSITORY - Submitted to Dwaraka Doss Goverdhan Doss Vaishnav College, Tamilnadu on 2025-05-05 20-07 3489785	1	Student Paper
6	drttit.gvet.edu.in	1	Publication
7	Submitted to Visvesvaraya Technological University, Belagavi	<1	Student Paper
8	REPOSITORY - Submitted to Exam section VTU on 2024-07-31 16-17 909490	<1	Student Paper
9	arxiv.org	<1	Publication
10	information-science-engineering.newhorizoncollegeofengineering.in	<1	Publication
12	www.intechopen.com	<1	Internet Data
14	Submitted to Visvesvaraya Technological University, Belagavi	<1	Student Paper
15	www.ncbi.nlm.nih.gov	<1	Internet Data

## APPENDIX B



**Fwd: International Conference for Women in Innovation, Technology and Entrepreneurship(ICWTE 2025) : Submission (1482) has been edited.**

1 message

Sou <sojanya2003@gmail.com>  
To: Anusha N <anusha190803@gmail.com>

Fri, May 23, 2025 at 1:06 PM

----- Forwarded message -----  
From: Microsoft CMT <noreply@msr-cmt.org>  
Date: Thu, May 1, 2025 at 3:41 PM  
Subject: International Conference for Women in Innovation, Technology and Entrepreneurship(ICWTE 2025) : Submission (1482) has been edited.  
To: <sojanya2003@gmail.com>

Hello,

The following submission has been edited.

Track Name: Data Science, Engineering and Architecture

Paper ID: 1482

Paper Title: MULTIMODAL EMOTION DETECTION

**Abstract:**  
In recent years, affective computing has become a topic of considerable interest, driven by its ability to enhance several domains, such as mental health monitoring, human-computer interaction, and personalized advertising. The progress of affective computing has been extensively supported by the emergence of sub-domains such as sentiment analysis and emotion recognition. Furthermore, Deep Learning (DL) techniques have made significant advancements in the realm of emotion recognition, resulting in the emergence of Multimodal Emotion Recognition (MER) systems that are capable of effectively processing data from various sources, such as audio, video, and text. However, despite the considerable progress made, there are still several challenges that persist in MER systems. Moreover, existing surveys often lack a specific focus on MER and the associated DL architectures. To address these research gaps, this study provides an in-depth systematic review of DL-based MER systems. This review encompasses the recent state-of-the-art models, foundational theories, DL architectures, mechanisms for fusing multimodal information, relevant datasets, performance evaluation, and practical applications. Additionally, the study identifies key challenges and limitations in MER systems and suggests future research opportunities. The main objective of this review is to provide a thorough comprehension of the present cutting-edge MER, thus enabling researchers in both academia and industry to stay up to date with the most recent developments in this rapidly evolving domain.

Created on: Thu, 01 May 2025 10:09:22 GMT

Last Modified: Thu, 01 May 2025 10:10:54 GMT

**Authors:**

- soujanya2003@gmail.com (Primary)
- vinur9308@gmail.com
- sushmitha451@gmail.com

Secondary Subject Areas: Not Entered

**Submission Files:**  
paperproject.pdf (349 Kb, Thu, 01 May 2025 10:09:14 GMT)

Submission Questions Response: Not Entered

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