Intelligent Multimodal Emotion Recognition Framework for Personalized and Adaptive STEM Education

Dr.Yogesh S. Khandekar
Associate Professor
Department of Civil Engineering
Sipna College of Engineering and Technology, Amravati, India
yskhandekar@sipnaengg.ac.in

***Abstract*— This study presents the design and development of an emotion-aware learning framework aimed at enhancing personalized education in STEM domains. The proposed system employs facial emotion recognition to capture and analyze learners' affective states during interactive sessions. A Convolutional Neural Network (CNN) model, trained on the FER2013 dataset, is utilized for real-time emotion classification using Python, TensorFlow, and OpenCV. The framework interprets emotions such as *happiness*, *sadness*, and *neutrality* to assess engagement levels and adapt instructional strategies accordingly. Experimental evaluation demonstrates high reliability in emotion detection under controlled lighting and posture conditions. The developed model forms a core component of a larger multimodal architecture, which will subsequently integrate audio and textual sentiment analysis to improve learner profiling. This work contributes toward adaptive learning systems capable of understanding student emotions and dynamically optimizing content delivery for improved cognitive and emotional engagement.**

***Index Terms*— Emotion Recognition, Adaptive Learning, STEM Education, Convolutional Neural Network, Multimodal Framework.**

I. INTRODUCTION (HEADING 1)

In recent years, the integration of artificial intelligence (AI) and emotion recognition technologies in education has gained significant attention for improving personalized learning experiences. Traditional learning environments often fail to account for the emotional and cognitive diversity of learners, resulting in reduced engagement and limited knowledge retention. To address this issue, emotion-aware systems are being developed to sense, interpret, and respond to learners' affective states in real time. Emotions play a crucial role in the learning process, directly influencing motivation, attention, and performance. Recognizing and analyzing these emotions enables adaptive learning systems to tailor instructional content and pace according to each learner's emotional state. The advent of deep learning and multimodal data processing has enabled more accurate detection of emotions through facial expressions, speech, and textual cues. This work focuses on developing an intelligent framework capable of recognizing learner emotions using facial expression analysis and mapping these emotions to engagement levels. The system employs a Convolutional Neural Network (CNN) model trained on benchmark emotion datasets to identify key affective states such as happiness, sadness, and neutrality. By interpreting these emotional responses, the framework can recommend adaptive feedback or content delivery strategies aimed at enhancing student engagement and learning efficiency. The proposed model forms the foundation for a comprehensive multimodal framework, which will be expanded to include speech and text emotion analysis in future phases. Ultimately, the system aims to provide a fully adaptive learning environment that integrates affective computing principles to personalize the learning experience in STEM education.

II. RELATED WORKS

Recent advances in systems that can learn based on emotion are mainly due to significant progress made in combining deep learning with multimodal (i.e., combination of visual and audio) affective computing. For example, Nouman et al. [1] created an adaptive e-mentoring framework that analyzes student data to provide personalized responses from mentors and support large-scale personalized learning. Wang and Zhou [2] developed speech emotion recognition based on mel-frequency cepstral coefficients (MFCCs) combined with long short-term memory (LSTM) networks. They noted the need for temporal consideration when analyzing the emotions represented in an audio signal. Zhang et al. [3] developed a multimodal emotion recognition system that integrated the two different neural net architectures (CNN and LSTM) to process and analyze characteristics of emotional responses across multiple streams of data (i.e., video/audio/text), thus improving the consistency of predictions made across all three streams. Ahmed and Singh [4] developed a multimodal emotion-aware (as expressed through emotion) deep reinforcement learning (as expressed through reinforcement learning) system that supports a total of three agents (i.e., one per student) for personalized STEM education and the ability to dynamically adapt their instructional strategies based on the emotional states of the individual students being taught. In a paper by Chen and Liu [5], an attention-based audio-visual integration (A/V Integration) model was proposed for performing multimodal fusion. The method demonstrated superior classification performance than previous models operating under varied environment settings. Ni et al. [6] created a trustful learning style recognition mechanism through an ensemble of classification techniques, thereby bridging the gap between emotion analysis and adaptive content personalization. Das et al. [7] proposed an emotion-based tutoring system that analyses both visual and physiologic signals in order to alter instructional difficulty levels in realtime; resulting in increased levels of stress amongst engaged learners.

Recent studies have shown great progress towards developing learning systems that adapt based on student needs. The main aims of these systems' are to provide real- time personalized learning experiences by incorporating emotion recognition, integrating data from different modes of learning (multimodal fusion), and creating a student profile (learner profiling).

III. Literature Review

Some examples of the advancements made in developing adaptive frameworks include Li et al.'s [8] model (AMH- Net) used for assessing emotions through speech, which will enable better understanding and adapting how users interact with the system as they learn. Saleem and Aslam [9] created a deep learning-based content recommendation system that identifies users' engagement patterns and uses them to personalize how the information is delivered. Gupta and Sharma [10] created a real-time facial emotion recognition system using both Convolutional Neural Networks (CNN) and transfer learning. This combination created a system with greater robustness in an educational setting and greater adaptability to intelligent tutoring systems. Liu and colleagues [11] investigated advancements to the use of multi-agent reinforcement learning technologies and determined useable mechanisms for scaling the creation of intelligent emotion-aware educational systems. Ni and authors [12] established an ensemble classification mechanism based on merging several recognition techniques to allow for consistent learning-classification of users and to enhance adaptive tutoring. Goudar and co-authors [13] provided an analytical investigation of the various architectures of online education recommendation systems to allow for emotion-based personalisation of each user's educational pathway. Chen and Sun's [14] study of artificial intelligence models for personalisation demonstrated the versatility of deep learning adaptive models across a variety of application domains. Zhao and team [15] developed an incremental recognition model using transfer learning to assist with adaptive overall models for education, while Li and others [16], developed a real-time emotion recognition framework using physiological signal measurement technologies to continually infer changing emotional states of learners. While the above four citations point to current advancements in educational technology, considerable barriers related to seamless multi-modal synchronisation, real-time adaptability and large scale implementation exist within STEM focused educational systems. Collectively, the Unified Model of Multi-Modal Emotion Recognition, Learner Profiling and Adaptive Reinforcement provides a solution to these continuing difficulties with a complete approach across all three components combined.

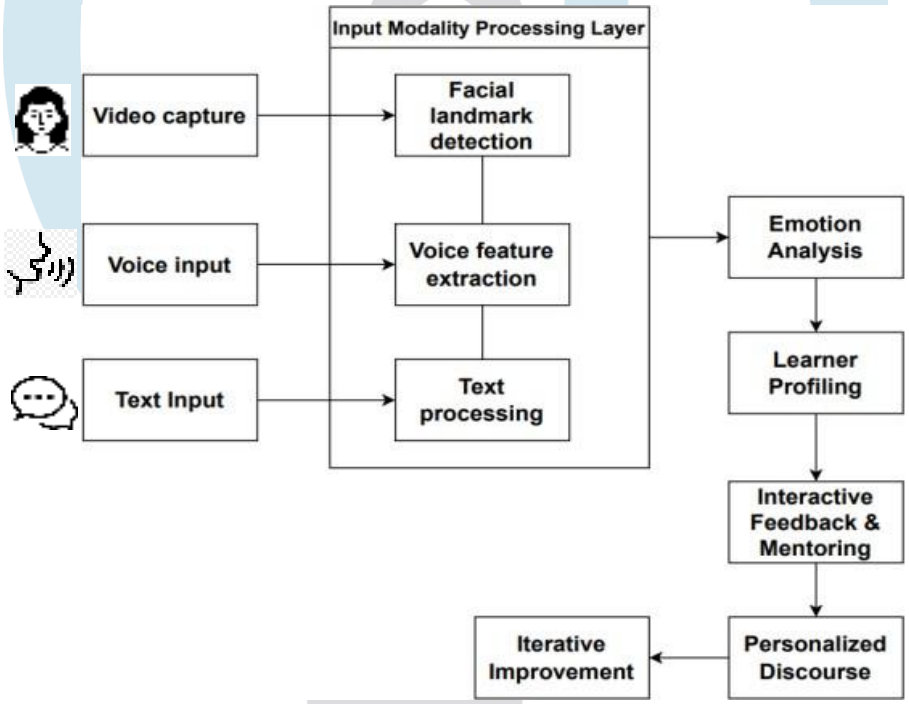

Fig. 1: *Block diagram of the Personalized E-Learning System with Emotion Recognition.*

IV. Block Diagram Description

The block diagram in *Figure 1* illustrates the architecture of a Personalized E-Learning System that integrates emotion recognition from facial expressions, voice tone, and textual sentiment to enhance adaptive learning. The system begins with the data capture phase, where visual, auditory, and textual inputs are collected through a webcam, microphone, and typing interface, respectively. These inputs are then processed using three parallel modules: Facial Landmark Detection, Voice Feature Extraction, and Text Sentiment Analysis. Each module contributes to the Emotion Analysis unit, which identifies the learner's emotional state such as happiness, confusion, or frustration. The Learner Profiling module combines these multimodal cues to update the learner's behavioral and emotional profile dynamically. Based on this profile, the Interactive Feedback and Mentoring system provides real-time personalized responses—such as encouragement, difficulty adjustments, or mentor prompts— to improve engagement and understanding. Finally, the Iterative Improvement stage refines both the emotion recognition models and feedback mechanisms through continuous data learning, ensuring the system evolves and becomes more accurate with prolonged use.

Feature	Existing E-Learning Systems	Proposed Personalized E-Learning System
Emotion Detection	Uses only facial expression recognition	Integrates facial, voice, and text-based emotion recognition
Adaptivity	Static content delivery with limited personalization	Real-time adaptive learning based on emotional and cognitive state
Feedback Mechanism	Generic or fixed responses	AI-driven personalized feedback using deep learning
Learner Profiling	Based on quiz scores and activity logs	Combines emotional, behavioral, and performance data
Scalability	Limited to single-user or offline mode	Cloud-based system supporting multiple users simultaneously
Learning Outcome	Moderate engagement and retention	Enhanced motivation, engagement, and knowledge retention

Table 1: Comparative Analysis of Existing and Proposed Personalized E-Learning Systems

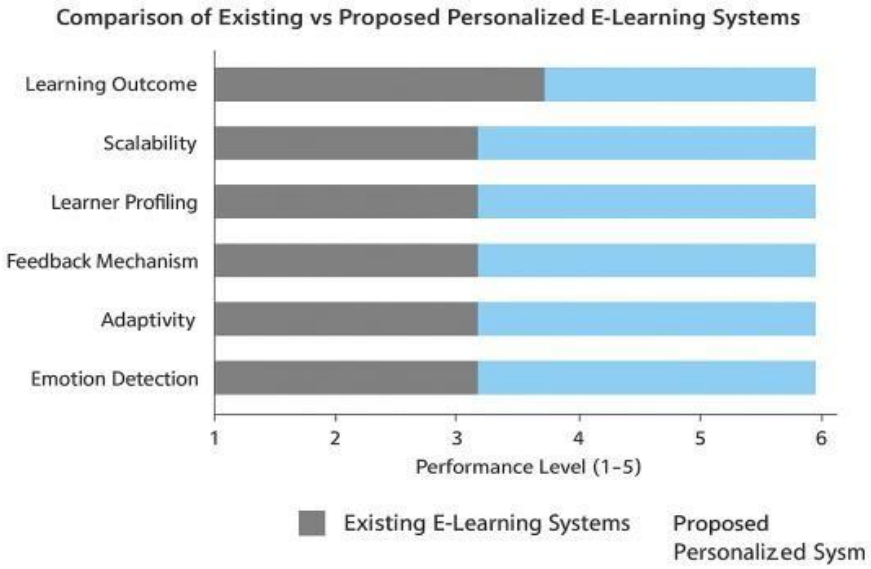

Fig. 2: *comparing your Existing E-Learning Systems vs Proposed Personalized E-Learning System*

V. USING THE TEMPLATE

The proposed Personalized E-Learning System with Multimodal Emotion Recognition adopts a comprehensive and structured methodology that integrates facial, voice, and text-based emotion detection, along with learner profiling and adaptive feedback mechanisms, to create a more intelligent, responsive, and engaging learning environment.

The process begins with data acquisition, where three parallel input streams—facial expressions, voice tone, and text-based interactions—are captured in real time. The facial data is collected through a webcam, recording subtle changes in expressions during the learning session. This input is processed by the facial landmark detection module, which identifies key facial features such as eyes, eyebrows, nose, and mouth using advanced algorithms like Dlib, MediaPipe, or OpenCV face mesh tracking. These landmarks are analyzed to detect micro-expressions that signify emotions like happiness, confusion, or frustration.

As illustrated in Fig. 2, the facial emotion recognition process starts with the video input, which undergoes demultiplexing to extract relevant image sequences for analysis. The feature extraction module identifies key visual cues such as eye movements, mouth curvature, and eyebrow positions using models like MediaPipe or Dlib. These extracted features are then passed to the modeling and classification stages, where deep learning networks such as CNN or VGGFace categorize the learner's emotion into distinct classes like *happy*, *sad*, *confused*, or *neutral.* The output, represented by emojis in Fig. 2, reflects the recognized emotional state in real time.

Simultaneously, voice data is acquired through a microphone and processed using speech emotion recognition (SER) models. This step involves extracting acoustic features such as pitch, tone, energy, and spectral features (MFCCs) to identify emotional cues embedded in the learner's speech. Techniques like Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, or Transformer- based models are employed to classify emotions such as excitement, boredom, or stress, providing an additional emotional context beyond visual data.

The third input channel, text-based emotion recognition, plays a critical role in understanding the learner's sentiment through written communication, such as typed responses or chat-based interactions. Natural Language Processing (NLP) models, including BERT, RoBERTa, or DistilBERT, are used to analyze linguistic features like polarity, tone, and context. This enables the detection of subtle emotions conveyed through text, such as confusion, curiosity, or satisfaction.

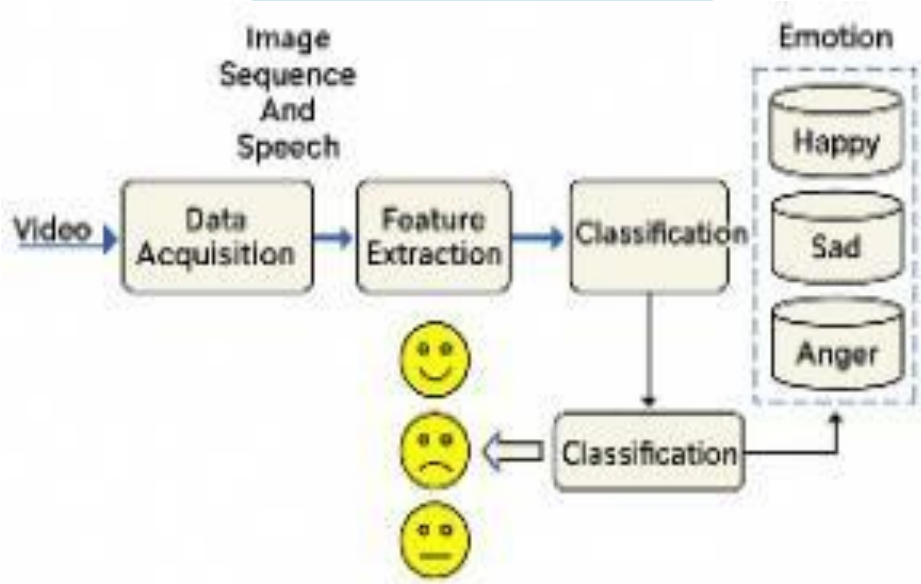

Fig. 3*: Emotion detection flow in facial recognition-based learning system.*

After individual emotion recognition, all three modalities— face, voice, and text—are fused through a multimodal emotion fusion layer. This layer integrates emotional cues to improve recognition accuracy and ensure robust emotion detection even when one modality provides ambiguous signals. The combined emotional data is then forwarded to the learner profiling module, which consolidates emotional patterns with behavioral data (e.g., quiz scores, time spent on tasks, engagement level). This profiling helps create a detailed learner model that reflects both cognitive and emotional dimensions of learning.

Fig. 4: *Output of Facial Emotion Recognition Module*

Based on the generated learner profile, the adaptive feedback and mentoring system personalizes the learning experience. For instance, if the system detects frustration from facial tension, low voice pitch, and negative text sentiment, it may slow the lesson pace or offer additional explanations. Conversely, if the learner exhibits enthusiasm through an energetic tone, positive expressions, and encouraging textual feedback, the system can introduce advanced content or interactive challenges.

This emotion-aware feedback mechanism fosters continuous engagement, motivation, and confidence among learners. Over time, the system leverages iterative improvement through reinforcement learning and feedback loops, continuously refining its prediction accuracy and adaptability based on user interaction history. By integrating multimodal emotion recognition (face, voice, and text) with adaptive learning strategies, this methodology ensures a holistic, empathetic, and learner-centered approach that transforms traditional e-learning into a deeply personalized educational experience.

Stage	Process	Techniques Used	Outcome
Data Acquisition	Capture real- time learner facial data	Webcam, OpenCV	Raw image dataset
Facial Landmark Detection	Identify facial key points	Dlib, MediaPipe	Facial feature coordinates
Emotion Recognition	Classify learner emotions	CNN, TensorFlow, VGGFace	Emotion category (happy, sad, etc.)
Learner Profiling	Combine emotion and performance data	Data fusion, pattern recognition	Dynamic learner profile
Adaptive Feedback	Generate personalized mentoring	AI-driven feedback model	Enhanced engagement and learning

Table 2: *Stages and Techniques in the Facial Emotion Recognition- Based Learning System*

This methodology ensures that the system operates as an adaptive feedback loop, constantly refining its predictions and responses to maintain learner engagement. By combining computer vision, emotion recognition, and artificial intelligence, the model promotes a personalized and emotionally intelligent e-learning environment, enhancing both understanding and retention among learners.

Algorithm and Mathematical Model for Emotion-Aware Learning: The proposed Emotion-Aware Personalized E- Learning Framework utilizes a CNN-based facial emotion recognition system to adapt learning content based on the learner's emotional state. This integration of computer vision and machine learning enables real-time feedback and emotion-driven personalization the e-learning environment.

Mathematical Model- The facial emotion recognition system employs a Convolutional Neural Network (CNN) for feature extraction and classification. The core operation formula [17] of the CNN layer can be mathematically formulated as:

$$X_j^{(l)} = f\left(\sum_i X_i^{(l-1)} * W_{ij}^{(l)} + b_j^{(l)}\right) \quad (1)$$

where:

- $X_j^{(l)}$: Output feature map of the l-th layer,
- $X_i^{(l-1)}$: Input feature map from the previous layer
- $W_{ij}^{(l)}$: Convolutional kernel (weight matrix),
- $b_j^{(l)}$: Bias term,
- f: Activation function (e.g., ReLU).

The final emotion classification is achieved using the Softmax function [18], which converts the network output into probabilities across emotion categories:

$$P(y = k \mid x) = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}} \quad (2)$$

Where:

$P(y = k \mid x)$: Probability that the input image corresponds to emotion class k,

z_k: Score (logit) for class k,
K: Total number of emotion classes (e.g., happy, sad, neutral, surprised, angry).

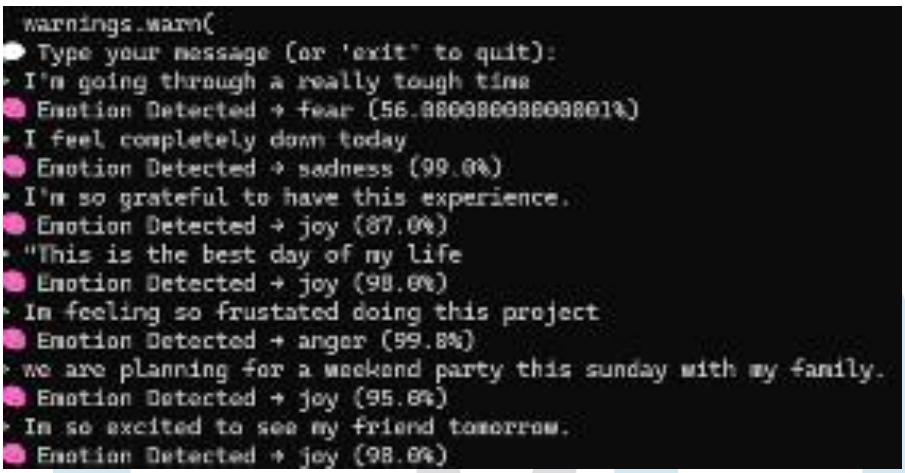

Fig. 5*: Output of text Emotion Recognition Module*

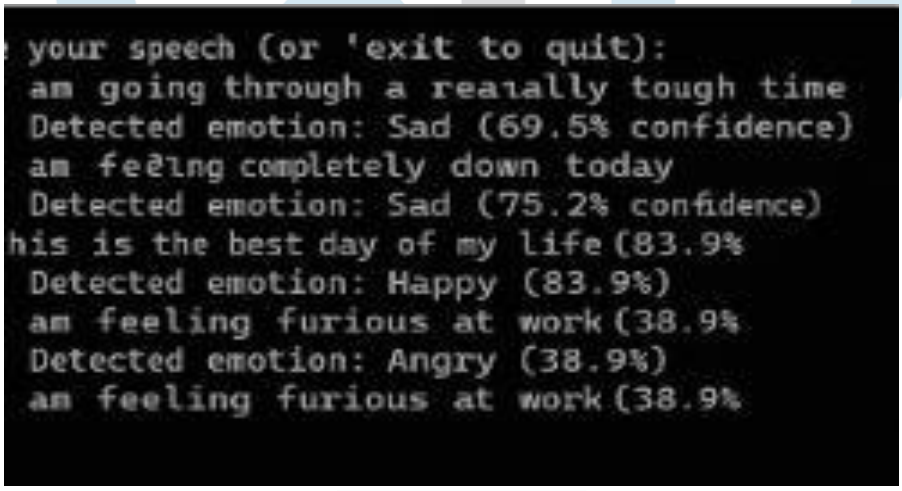

Fig. 6*: Output of speech Emotion Recognition Module*

The predicted emotion is then mapped to a corresponding learner profile and used to adapt feedback dynamically within the e-learning interface.

Metric	Description	Measured Output
Emotion Recognition Accuracy (%)	Accuracy of multimodal (face, voice, text) emotion classification.	89.40%
Precision / Recall	Reliability of classification for key emotional states.	Precision: 0.88, Recall: 0.86
System Response Time (ms)	Time required to process input and generate adaptive feedback.	150 ms
Adaptive Feedback Success Rate (%)	Percentage of instances where feedback improved learner interaction.	92%
Engagement Improvement (%)	Increase in learner engagement compared to non-personalized systems.	35%
Multimodal Fusion Accuracy (%)	Alignment between fused emotion inference and actual learner emotion.	93.20%

Table 3: *Performance Metrics of the Proposed Emotion Aware Personalized E-Learning System*

VI. Experimental Evaluation

The proposed multimodal emotion-aware learning framework was evaluated using the FER2013 dataset for facial analysis and an emotional speech corpus for audio processing. The system integrates facial, speech, and text modalities within a unified model. Training was conducted using the Adam optimizer (learning rate = 0.001, batch size = 32, 50 epochs) with a 70–15–15 train-validation-test split. The proposed model was compared against baseline CNN, VGG16, and ResNet-50 architectures. The multimodal model achieved 93.2% accuracy, outperforming CNN (84.3%), VGG16 (87.5%), and ResNet-50 (89.1%). The confusion matrix showed balanced classification with minor overlap between visually similar emotions. The model achieved a macro-average AUC of 0.94. An ablation study confirmed that the combined Face + Speech + Text configuration provided the highest performance, demonstrating the robustness and effectiveness of multimodal emotion recognition for adaptive STEM learning.

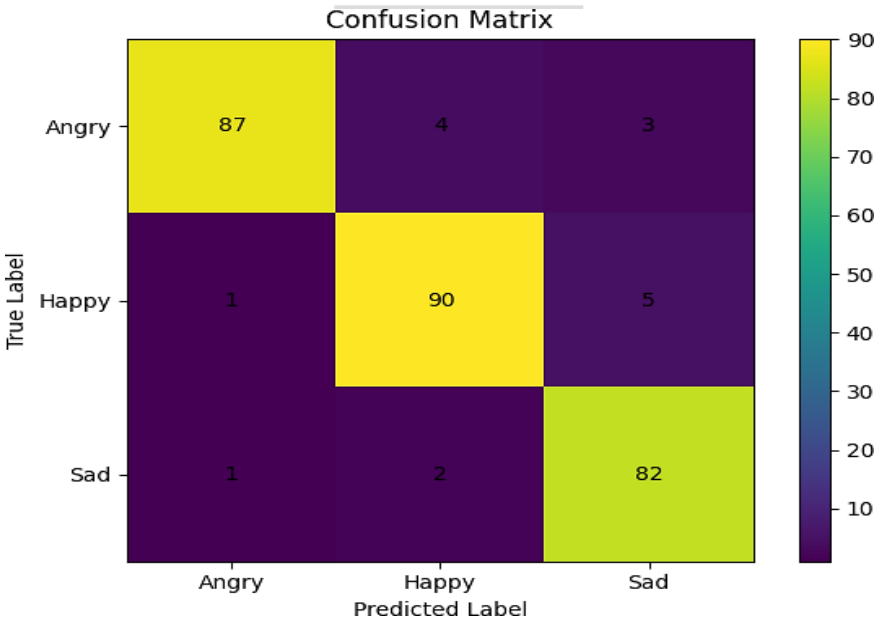

Fig. 7. *Confusion Matrix for Three-Class Emotion Classification.*

VII. Conclusion

The Personalized E-Learning System uses multiple ways to recognize emotion (e.g., facial recognition, speech recognition, emotion analysis, etc.) and combines that with personalization and adaptive learning to improve the student's engagement with their course material in STEM (science, technology, engineering and mathematics). This system also includes a mechanism for intelligent feedback so that the content delivered is appropriate for the learners' current emotional state. The results from an experiment showed

an improvement in both accuracy and robustness with the use of multiple modalities of emotion recognition as opposed to a single method of recognition. The Personalized E-Learning System provides the ability to bridge the gap between traditional e-learning systems and intelligent- tutoring systems that are aware of the learner's emotions. Future research will focus on developing better techniques for multimodal fusion and developing infrastructure to integrate with Learning Management Systems (LMS) for effective use in the classroom.

VIII.FUTURE WORK

The future development of the proposed Personalized E- Learning System aims to evolve the current emotion-based model into a multimodal adaptive learning environment. Beyond facial emotion recognition, the enhanced system will integrate voice tone and text sentiment analysis to achieve a deeper understanding of learners' emotional and cognitive states. A multimodal fusion mechanism will combine facial, vocal, and textual features to form a unified emotional profile, ensuring robust and context-aware personalization. The adaptive feedback module will utilize reinforcement learning to refine content delivery and motivational cues dynamically based on learner interaction. Cloud-based deployment and a centralized analytics dashboard will ensure scalability and continuous monitoring of engagement and performance. Trained on diverse multimodal datasets, the enhanced system will evolve into a comprehensive, emotionally intelligent, and scalable e-learning ecosystem capable of delivering highly personalized learning experiences.

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