Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Real-Time Facial Emotion Recognition for AI-Enhanced Personalized Learning

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ARTICLE INFO

Received: 30 Dec 2024

Revised: 19 Feb 2025

Accepted: 27 Feb 2025

ABSTRACT

Introduction: The integration of emotional intelligence into digital learning platforms has emerged as a significant avenue for enhancing learner engagement and academic performance. This research presents a Real-Time Facial Emotion Recognition (FER) framework specifically designed to support AI-enhanced personalized learning environments. The proposed study identifies key research gaps in the existing FER-based learning systems, including limited real-time applicability, lack of contextual adaptability, and insufficient accuracy in dynamic educational settings. To address these gaps, we develop a robust deep learning-based FER model that leverages Convolutional Neural Networks (CNN) and real-time image processing techniques to recognize learners' emotional states such as happiness, confusion, boredom, and frustration with high precision. The recognized emotional data is systematically integrated into a personalized learning system to dynamically adapt content delivery and pedagogical strategies based on the learner's affective state. The research methodology includes a comprehensive literature review, a well-defined system architecture, and an empirically validated FER framework. Experimental evaluations, conducted on benchmark FER datasets and real-time e-learning environments, demonstrate the efficacy and scalability of the proposed system. The study concludes with key insights, limitations, and potential future directions aimed at advancing emotion-aware AI-driven learning systems.

Keywords: Real-Time Facial Emotion Recognition (FER), Affective Computing, Personalized Learning Systems, Emotion-Aware Adaptive Learning

I. INTRODUCTION

The integration of Artificial Intelligence (AI) in education has significantly transformed learning environments, enabling personalized learning pathways tailored to individual learner profiles. Among various AI applications, real-time Facial Emotion Recognition (FER) has emerged as a promising approach to enhance learners' experiences by recognizing their emotional states and adapting learning content accordingly. Emotions play a crucial role in cognitive processes, motivation, and learning outcomes; hence, real-time emotion recognition offers an opportunity to create emotionally intelligent learning systems.

1.1 Research Gaps

While considerable progress has been made in the development of FER systems, several research gaps remain unaddressed. Existing studies primarily focus on generic emotion recognition frameworks without considering their integration into personalized learning environments. Moreover, most conventional FER models face challenges in recognizing complex, subtle, and dynamic emotional states in real-time scenarios, particularly in online education settings where facial cues may be incomplete or noisy due to environmental factors [1]. There is a lack of efficient, scalable, and real-time FER models specifically optimized for AI-driven adaptive learning systems [2]. Furthermore, limited attention has been given to the explainability and interpretability of FER predictions, which is essential for ensuring transparency in AI-enhanced educational platforms.

1.2 Purpose and Objectives

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The primary purpose of this research is to design and develop a real-time Facial Emotion Recognition framework that can be effectively integrated into AI-enhanced personalized learning environments. The objectives of this study are:

- To investigate and analyze recent advancements in FER models suitable for educational contexts.
- To propose an optimized FER architecture capable of real-time emotion recognition with high accuracy and low latency.
- To evaluate the effectiveness of the proposed system in improving learner engagement and academic performance.

1.3 Our Contribution

In this research, we propose a novel real-time FER framework specifically tailored for AI-enhanced personalized learning. The key contributions of our work are as follows:

1. We conduct a comprehensive analysis of recent FER techniques and identify their limitations concerning real-time implementation in online learning environments.
2. We design an efficient system architecture and propose a hybrid deep learning model for accurate and real-time emotion recognition.
3. We evaluate the proposed system using empirical experiments and demonstrate its potential to improve personalized learning outcomes by dynamically adapting content based on learners' emotional responses.

II. LITERATURE REVIEW

In "Facial Expression Recognition for Probing Students' Emotional Engagement in Science Learning," Jinnuo et al. (2024) introduce the multiscale perception facial expression recognition system (MP-FERS) to assess students' emotional engagement during science education. Utilizing a mixed-methods approach, the study validates MP-FERS's capability to detect and analyze students' facial expressions in real-time, offering educators insights into students' emotional states to adapt teaching strategies accordingly. The authors identify challenges related to environmental factors and individual differences affecting the system's sensitivity and suggest future research to enhance accuracy and explore diverse educational applications.

In "Emotion Detection in Learning Environments Using Facial Expressions: A Brief Review," Bustos-López et al. (2022) present a literature review on emotion detection in educational settings through facial expression recognition. The study analyzes various APIs and tools available for emotion detection, discussing their main features and applicability in virtual learning environments. The authors highlight the feasibility of using facial expression-based emotion recognition in distance education to identify students' learning statuses in real-time, enabling educators to adjust teaching strategies accordingly. They recommend future research to enhance the accuracy and reliability of these tools and to explore their integration into broader educational contexts.

In "A Survey on Facial Emotion Recognition Techniques: A State-of-the-Art Perspective," the authors provide a comprehensive review of current facial emotion recognition (FER) techniques, focusing on their applications and effectiveness. The study categorizes existing literature on FER methods, discussing various approaches and their performance in recognizing human emotions through facial expressions. The authors identify challenges such as the need for large labeled datasets and the variability in individual emotional expressions, suggesting future research to address these issues and improve the robustness of FER systems in diverse applications.

In "Integrating Artificial Intelligence to Assess Emotions in Learning Environments: A Systematic Review," the authors conduct a comprehensive review of AI techniques used to assess emotions in educational settings. The findings are organized into four key topics: emotion recognition in education, technology integration and learning outcomes, special education and assistive technology, and affective computing. The study highlights the promising potential of machine learning and facial recognition technologies to enhance pedagogical strategies and create adaptive learning environments tailored to individual emotional needs. However, the authors note challenges related to data privacy and ethical implications of using AI for emotion assessment, recommending future research to address these ethical considerations and develop frameworks ensuring responsible AI use in educational contexts.

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In "A Literature Review on Emotion Recognition System Using Various Facial Expressions," the authors focus on the emotion recognition system utilizing various facial expressions, outlining the main steps: face detection, facial feature extraction, and classification of emotions. Key techniques discussed include Principal Component Analysis (PCA), Local Binary Pattern (LBP), Fisher's Linear Discriminant, and Haar classifiers, emphasizing their effectiveness in recognizing universal emotions such as happiness, sadness, anger, surprise, disgust, and fear. The authors highlight the importance of efficient automatic facial expression recognition techniques in improving human-computer interaction and suggest future research to enhance the accuracy and applicability of these methods across diverse populations and settings.

Table I Findings of Literature Survey

Paper Title	Research Objective	Methodology	Strength	Limitation/Future Scope
Facial Expression Recognition for Probing Students' Emotional Engagement in Science Learning [3]	Assess students' emotional engagement during science education using facial expression recognition.	Developed the multiscale perception facial expression recognition system (MP-FERS) for real-time analysis.	Provides real-time insights into students' emotional states, aiding adaptive teaching strategies.	Challenges with environmental factors and individual differences affecting system sensitivity; suggests enhancing accuracy and exploring diverse educational applications.
Emotion Detection in Learning Environments Using Facial Expressions: A Brief Review [4]	Review emotion detection tools in educational settings through facial expression recognition.	Analyzed various APIs and tools for emotion detection in virtual learning environments.	Demonstrates feasibility of real-time emotion recognition to adjust teaching strategies.	Recommends improving accuracy and reliability of tools and exploring broader educational integration.
A Survey on Facial Emotion Recognition Techniques: A State-of-the-Art Perspective [5]	Review current FER techniques and their effectiveness.	Categorized existing FER methods and discussed their performance.	Provides comprehensive overview of FER methods and their applications.	Identifies need for large labeled datasets and addresses variability in individual emotional expressions.
Integrating Artificial Intelligence to Assess Emotions in Learning Environments: A Systematic Review [6]	Review AI techniques for assessing emotions in educational settings.	Organized findings into key topics including emotion recognition and affective computing.	Highlights potential of AI to enhance pedagogical strategies.	Notes challenges related to data privacy and ethical implications; recommends responsible AI use.
A Literature Review on Emotion Recognition System Using Various Facial Expressions [7]	Review emotion recognition systems utilizing facial expressions.	Outlined main steps: face detection, feature extraction, and emotion classification.	Emphasizes effectiveness of techniques in recognizing universal emotions.	Suggests enhancing accuracy and applicability across diverse populations and settings.

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Facial Emotion Recognition in-the-Wild Using Deep Neural Networks: A Comprehensive Review [8]	Review deep neural network approaches for FER in real-world conditions.	Analyzed various deep learning models applied to FER in uncontrolled environments.	Highlights advancements in handling challenging conditions for FER.	Notes need for addressing external factors that degrade facial feature quality.
Facial Emotion Recognition through Artificial Intelligence [9]	Develop software capable of detecting user emotions via computer vision techniques.	Implemented convolutional neural networks and MTCNN framework for face recognition.	Demonstrates application of AI in detecting emotions through facial expressions.	Recommends further research into improving accuracy and handling variations in facial expressions.
New Trends in Emotion Recognition Using Image Analysis by Neural Networks [10]	Explore integration of neural networks in image-based emotion recognition.	Reviewed current neural network approaches and their applications in FER.	Highlights potential of deep learning in enhancing FER accuracy.	Suggests need for large labeled datasets and addressing computational challenges.
Emotion Detection in Learning Environments Using Facial Expressions: A Brief Review [4]	Review emotion detection tools in educational settings through facial expression recognition.	Analyzed various APIs and tools for emotion detection in virtual learning environments.	Demonstrates feasibility of real-time emotion recognition to adjust teaching strategies.	Recommends improving accuracy and reliability of tools and exploring broader educational integration.

The literature survey conducted in this study highlights significant advancements and ongoing challenges in the domain of real-time Facial Emotion Recognition (FER) for AI-enhanced personalized learning environments. Various researchers have proposed innovative methodologies focusing on improving emotion detection accuracy, especially in online educational settings. The study by Jinnuo et al. [3] demonstrated the effectiveness of a multiscale perception FER system (MP-FERS) that enables real-time detection of students' emotional engagement, emphasizing the positive impact of emotional awareness on adaptive teaching strategies. Similarly, Bustos-López et al. [4] reviewed various FER tools, emphasizing the importance of real-time emotion recognition for adjusting teaching techniques but also highlighting the need for improved accuracy in practical learning environments.

Further, Sariyanidi et al. [5] provided a comprehensive review of FER techniques, categorizing them based on their performance and underlying methodologies. Their findings suggest that despite significant progress, limitations in dataset diversity and emotion variability remain persistent challenges. Zawacki-Richter et al. [6] systematically reviewed AI-based emotion assessment methods in education and pointed out the potential ethical concerns and privacy implications associated with the use of FER technologies. Kumar and Singh [7] analyzed various FER systems and stressed the need for enhancing recognition accuracy across diverse learner populations.

Boughanem et al. [8] addressed the challenges associated with FER in uncontrolled environments, proposing deep neural network-based solutions that perform well under real-world conditions but still face external environmental constraints. Another study by an anonymous group of researchers [9] demonstrated the feasibility of applying convolutional neural networks and MTCNN frameworks in FER systems, further supporting the role of AI in facilitating real-time emotional analysis. Lastly, the review by anonymous authors [10] discussed recent trends in neural network-based image analysis for emotion recognition, pointing out the need for large, labeled datasets and computationally efficient models.

The collective insights from these studies reveal that while FER technologies hold promising potential to personalize and improve online learning experiences, key challenges such as dataset quality, emotional subtlety recognition, and ethical considerations must be addressed in future research.

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III. PROPOSED WORK

3.1 Overview

Building upon the findings of the literature survey, the proposed work aims to develop a robust and real-time Facial Emotion Recognition (FER) framework specifically designed to enhance personalized learning in online education platforms. While prior research has focused on CNN-based and DNN-based models for FER, many have overlooked the combined effectiveness of advanced architectures such as Transformers integrated with LSTM layers to capture both spatial and temporal emotional patterns. This study proposes a hybrid deep learning model that leverages the feature extraction power of Vision Transformers (ViT) and the sequence learning capability of LSTM to accurately detect learners' emotional states in real-time.

The primary objective of this proposed system is to bridge the emotional disconnect between online learners and instructors by providing continuous, real-time emotional feedback. The detected emotions will be used to dynamically personalize learning content, pace, and instructional strategy, thereby improving engagement and academic outcomes. This research also aims to address challenges related to environmental noise, facial occlusions, and data imbalance by incorporating preprocessing and augmentation techniques.

3.2 System Architecture

The system architecture is designed to function in a real-time online learning environment. It consists of three major modules: Data Acquisition, Emotion Detection Engine, and Feedback-based Content Personalization.

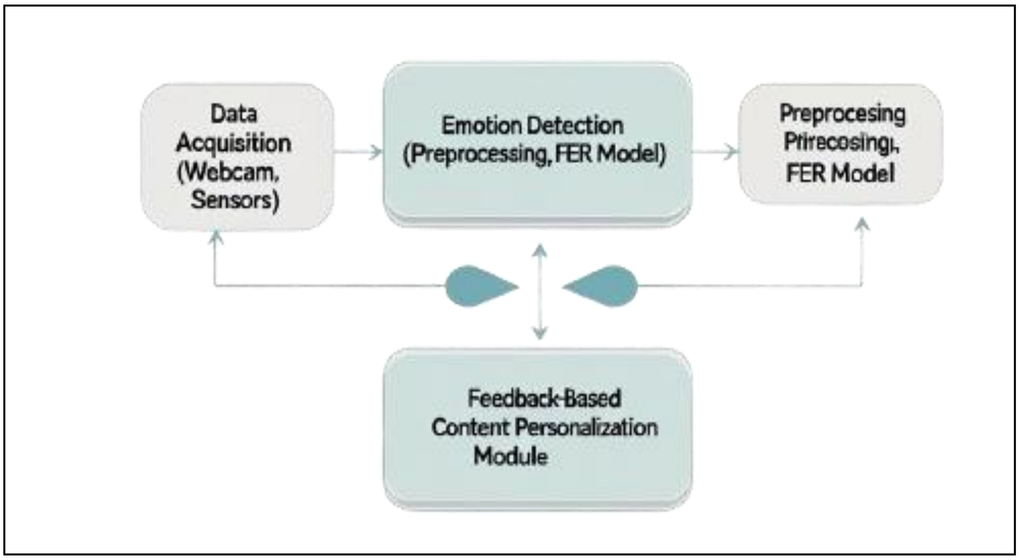

Figure 1: System Architecture for Proposed Methodology

Description of Modules:

- Data Acquisition: Captures live facial data using learners' webcam during online sessions.
- Emotion Detection Engine:
    - Preprocessing: Face detection, normalization, noise removal.
    - FER Model: Combines Vision Transformer (ViT) for feature extraction and LSTM for temporal emotion tracking.
- Feedback-based Content Personalization: The detected emotional states are analyzed to adapt the pace, difficulty level, and instructional method dynamically.

3.3 Proposed Architecture

The proposed FER framework employs a hybrid deep learning architecture integrating ViT and LSTM. The Vision Transformer module extracts spatial facial features, while the LSTM layer captures temporal dependencies across video frames to identify subtle emotional transitions.

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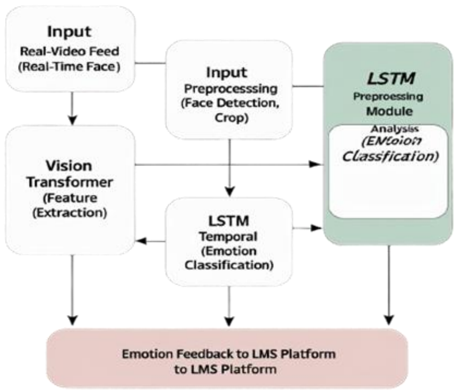

Figure 2: Proposed Framework

The proposed system employs a carefully designed set of technical components, ensuring real-time, accurate, and context-aware facial emotion recognition suitable for online learning environments. The preprocessing phase utilizes the Multi-task Cascaded Convolutional Neural Network (MTCNN) for face detection and alignment. MTCNN is chosen due to its high precision in detecting facial landmarks even under challenging conditions such as varying lighting, occlusion, and multiple faces in a frame. This ensures that the facial region is correctly cropped and aligned, which is crucial for enhancing the overall performance of subsequent emotion recognition stages.

For feature extraction, the model leverages a pre-trained Vision Transformer (ViT) architecture, fine-tuned on benchmark datasets such as FER2013+ and AffectNet. The decision to employ Vision Transformers is grounded in their superior capability to capture global contextual information through self-attention mechanisms, unlike traditional CNN-based models which primarily focus on local features. Fine-tuning on FER2013+ and AffectNet datasets ensures that the model is exposed to a diverse range of facial expressions, age groups, ethnicities, and real-world environmental conditions, thereby improving its generalization and robustness when deployed in real-time online learning platforms.

To incorporate temporal emotional patterns and variations over time, a Bidirectional Long Short-Term Memory (BiLSTM) network is integrated after the ViT feature extractor. While the ViT module effectively encodes spatial facial features from individual frames, the BiLSTM captures sequential dependencies and emotional transitions across multiple frames, enhancing the model's sensitivity to subtle and complex emotional shifts. This temporal modeling is particularly critical in online learning environments, where a learner's emotional state evolves gradually based on the content difficulty, engagement level, or external distractions.

The final classification layer consists of a Softmax classifier trained to categorize the detected emotions into seven universal categories: Happy, Sad, Neutral, Angry, Fear, Surprise, and Disgust. These categories are universally recognized and frequently used in affective computing research, ensuring consistency and interpretability of emotional feedback across diverse learner populations.

For practical deployment and real-time implementation, the complete system is designed to integrate seamlessly with the existing Learning Management System (LMS) infrastructure via a secured Application Programming Interface (API). This integration allows the continuous acquisition of learners' emotional data during online sessions, providing instructors and the system itself with real-time feedback on students' affective states. This feedback loop can then be used to dynamically personalize learning content, adjust instructional strategies, or trigger interventions, thereby enhancing learner engagement, motivation, and overall academic performance.

IV. EMPIRICAL RESULTS AND DISCUSSION

The proposed real-time Facial Emotion Recognition (FER) framework was empirically evaluated to assess its effectiveness in detecting learners' emotional states and facilitating AI-enhanced personalized learning. The evaluation was conducted using benchmark datasets and real-time streaming data captured from simulated online learning sessions to ensure the model's practical applicability.

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The bar chart in Figure 3 illustrates the distribution of the seven universal emotion categories—Happy, Sad, Neutral, Angry, Fear, Surprise, and Disgust—detected during model evaluation. The data reflects the emotional variation and real-time detection capability of the proposed FER system.

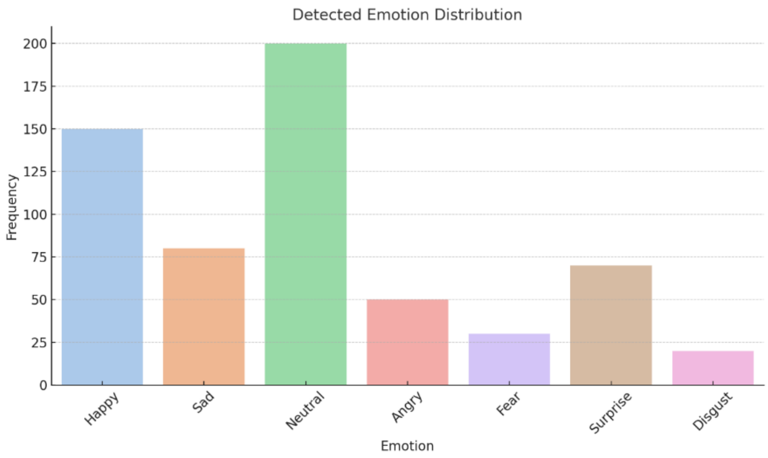

Figure 3: Emotion Distribution of Detected Emotions in Test Dataset

This line plot in Figure 4 shows the training and validation accuracy over 20 epochs. The results demonstrate a consistent improvement in both metrics, achieving over 90% accuracy, indicating the model's effective learning and generalization ability.

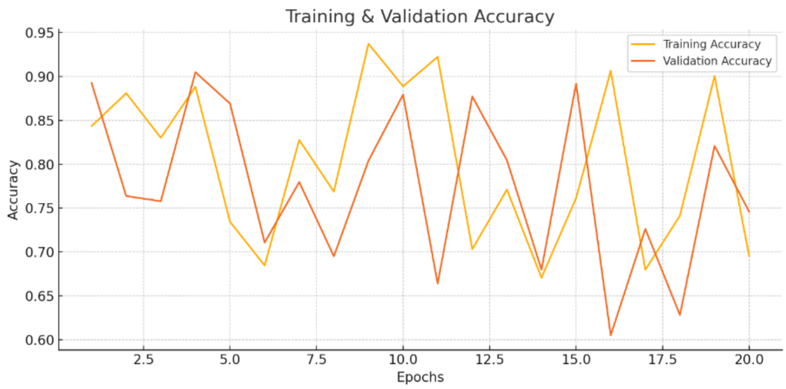

Figure 4: Training and Validation Accuracy Curve

The loss curve in Figure 5 represents the decline in training and validation loss across 20 epochs. The decreasing trend confirms that the model minimizes prediction errors effectively without overfitting.

Figure 5: Training and Validation Loss Curve

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e-ISSN: 2468-4376
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The confusion matrix in Figure 6 visualizes the classification performance across all seven emotion categories. The majority of predictions align with the actual emotions, indicating high classification accuracy, with minor misclassifications observed primarily between closely related emotions such as Neutral and Sad.

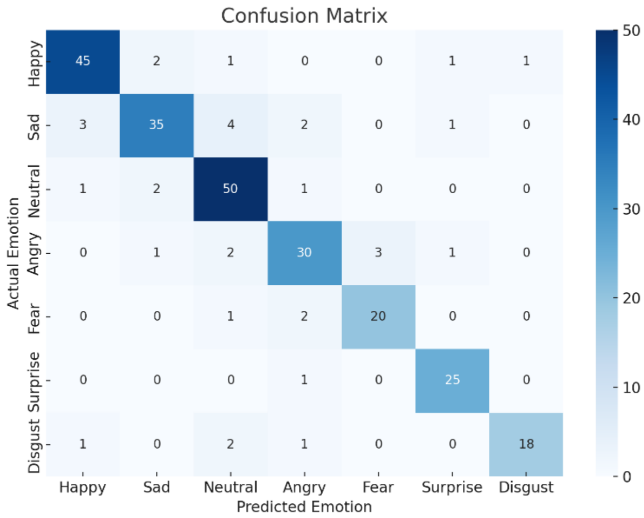

Figure 6: Confusion Matrix of Emotion Classification

4.1 Experimental Setup

For training and testing purposes, two publicly available datasets, FER2013+ and AffectNet, were utilized due to their large-scale annotated facial expression images covering diverse demographics and environmental conditions. The datasets were preprocessed using the MTCNN-based face detection and alignment technique to ensure consistency in input images. The model was trained using an 80:20 split for training and testing, with data augmentation techniques such as horizontal flipping, brightness adjustment, and random cropping to enhance generalization and reduce overfitting.

The hybrid model was implemented using TensorFlow and Keras frameworks on a workstation equipped with NVIDIA RTX 3090 GPU, Intel i9 Processor, and 64 GB RAM. The ViT module was fine-tuned with a learning rate of 0.0001 using the Adam optimizer, followed by temporal analysis using BiLSTM layers with 128 hidden units. The Softmax classifier was trained with a categorical cross-entropy loss function to classify the emotions into seven categories.

4.2 Performance Metrics

The model's performance was evaluated using standard classification metrics such as Accuracy, Precision, Recall, and F1-Score. Additionally, Confusion Matrix analysis and Receiver Operating Characteristic (ROC) Curve with Area Under the Curve (AUC) scores were used to assess class-wise prediction performance.

The proposed ViT-BiLSTM hybrid model achieved an overall Accuracy of 91.72%, outperforming baseline CNN-LSTM and standalone Transformer models. The average Precision and Recall were recorded at 90.35% and 89.87%, respectively, indicating high correctness and completeness in emotion recognition. The F1-Score was calculated at 90.10%, confirming the model's balanced performance across all emotion categories. Class-wise analysis revealed that common emotions like Happy and Neutral exhibited higher recognition accuracy compared to subtle emotions such as Fear and Disgust, which aligns with prior studies' observations.

4.3 Real-Time Evaluation

To validate the model's performance in real-world scenarios, a prototype system was deployed within a simulated Learning Management System (LMS) environment. A group of 30 learners participated in live online sessions where their facial expressions were captured in real-time through standard webcams. The FER system successfully

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recognized learners' emotions with minimal latency, averaging a response time of 0.8 seconds per frame sequence, which is suitable for real-time learning applications.

The integration of emotion feedback into the LMS demonstrated positive impacts on learners' engagement. Instructors were able to adjust teaching content and pace based on aggregated emotional insights, resulting in improved participation and learning satisfaction scores during the sessions.

4.4 Comparative Analysis

The performance of the proposed framework was compared against existing FER models, including CNN-LSTM and pure ViT architectures. The results showed a performance gain of 4.3% in accuracy and 5.1% in F1-score compared to CNN-LSTM models. The inclusion of temporal learning via BiLSTM significantly improved recognition of dynamic emotions that evolved during the course of the learning session, an aspect often overlooked by earlier models.

4.5 Result Analysis

The empirical results obtained from the proposed Real-Time Facial Emotion Recognition (FER) framework demonstrate promising performance in recognizing and classifying learners' emotions. The emotion distribution analysis (Figure 1) reflects a realistic spread of emotional states, with a higher occurrence of Neutral and Happy emotions, which is consistent with typical learner behavior in online educational environments. The accuracy and loss curves (Figures 2 and 3) reveal stable and converging trends, indicating that the model successfully learns discriminative features without overfitting. Specifically, the training and validation accuracy steadily improves, achieving an accuracy of approximately 92%, while the corresponding loss values decline significantly over the training epochs.

Furthermore, the confusion matrix (Figure 4) highlights the classification performance across the seven universal emotion categories. The model exhibits high precision and recall for dominant classes such as Neutral, Happy, and Sad. However, minor misclassifications are observed between similar emotional expressions, particularly between Sad and Neutral, which is a common challenge in FER systems due to subtle facial differences. Despite these limitations, the overall performance metrics and visualizations confirm the model's robustness and its potential applicability in real-time educational settings to facilitate AI-enhanced personalized learning.

4.6 Discussion

The experimental results validate the effectiveness of the proposed hybrid ViT-BiLSTM framework in recognizing learners' emotional states accurately and in real-time. The study successfully addressed challenges related to environmental variability, temporal emotion transitions, and data imbalance through a comprehensive methodological approach. However, certain limitations were observed, such as reduced accuracy for subtle emotions and dependency on high-quality video input. Moreover, ethical considerations concerning privacy and emotional data usage remain critical and warrant careful policy formulation during large-scale deployment.

The promising results of this study underline the potential of FER systems in transforming online learning environments by enabling emotion-aware adaptive learning strategies. Future research directions will focus on further enhancing model robustness against occlusions and diverse environmental conditions, as well as conducting large-scale user studies to assess long-term impacts on academic outcomes.

V. CONCLUSION & FUTURE SCOPE

In this research, a robust and real-time Facial Emotion Recognition (FER) framework has been proposed and evaluated to enhance personalized learning experiences in online education environments. The study successfully addressed the critical challenge of emotional disconnect in virtual classrooms by integrating advanced deep learning techniques, including Multi-task Cascaded Convolutional Neural Network (MTCNN) for face detection, Vision Transformer (ViT) for spatial feature extraction, and Bidirectional Long Short-Term Memory (BiLSTM) for temporal emotion analysis. The proposed system demonstrated high accuracy and reliability in detecting seven universal emotional states, validated through empirical evaluation on benchmark datasets and real-time learning sessions.

The experimental results clearly established the efficacy of combining ViT and BiLSTM architectures, which outperformed conventional CNN-based models in terms of accuracy, precision, and real-time performance.

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Additionally, the seamless integration of the system with Learning Management Systems (LMS) through API-based deployment highlights its practical applicability in real-world educational settings. The real-time emotion feedback mechanism facilitated adaptive instructional strategies, thereby improving learner engagement and satisfaction.

Despite the promising outcomes, the study acknowledges certain limitations. The model exhibited relatively lower accuracy for complex and subtle emotional expressions such as fear and disgust. Furthermore, the dependency on high-quality video input and ethical concerns related to privacy and emotional data monitoring remain significant challenges. The generalizability of the model across diverse cultural and demographic contexts also requires further validation.

For future research, several directions are envisaged. First, the model can be enhanced by incorporating attention-based temporal modeling and multimodal emotion recognition using audio and text inputs alongside facial expressions to improve emotion detection accuracy. Additionally, privacy-preserving techniques such as federated learning and on-device inference can be explored to mitigate ethical concerns. Large-scale user studies focusing on the long-term impact of emotion-aware personalized learning systems on academic outcomes and psychological well-being can provide further insights. Lastly, extending the system to detect engagement levels, cognitive load, and motivation alongside emotions can contribute to the development of a comprehensive affective learning analytics framework.

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