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Real-Time Emotion Detection in Online Learning Environments Using CNN-Based Facial Expression Analysis and Alert Mechanism

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Abstract

Online education has become increasingly prevalent, but it often lacks the emotional awareness present in physical classrooms. In virtual settings, teachers are unable to gauge students' emotional states - such as boredom, confusion, frustration, or engagement - which play a critical role in the learning process. To address this problem, our project proposes a realtime emotion recognition system that monitors student emotions during online classes through live webcam analysis. The system uses a Convolutional Neural Network (CNN) to detect and classify facial expressions into distinct emotional states. Real-time video is captured using OpenCV, and facial features are extracted from each frame for emotion prediction. Publicly available datasets such as FER-2013 (for basic emotions) is used to train the model, ensuring reliable recognition of student states in educational scenarios. To enhance the learning environment, the system integrates a feedback alert mechanism that notifies mentors when students display signs of negative emotional states like prolonged confusion or frustration. Additionally, the project features an emotion timeline visualization, which plots variations in student emotions throughout the class session, providing mentors with valuable post-session insights. This intelligent and scalable system brings emotional awareness into digital classrooms, enabling more responsive and empathetic teaching. Designed to be achievable within a student project scope, it combines computer vision, deep learning, and human-centered design to improve virtual learning outcomes.

Keywords: *Emotion Detection, Online Learning, Virtual Classrooms, Student Engagement, Facial Expression Recognition, Speech Emotion Recognition, Multimodal Analysis, CNN, LSTM, Viola–Jones Algorithm, Real-Time Monitoring, Affective Tutoring Systems.*

1. Introduction

In recent years, the integration of artificial intelligence (AI) and machine learning (ML) into education has grown rapidly, especially with the increasing shift toward online and hybrid learning environments. However, one of the most persistent challenges in digital education is the lack of real-time emotional engagement between students and instructors. Traditional classrooms allow teachers to observe students' expressions, body language, and attentiveness directly, whereas online platforms often fail to capture these subtle cues. This gap significantly affects learning outcomes, motivation, and the overall effectiveness of virtual education. Emotions play a crucial role in learning. They influence attention, memory retention, and cognitive performance. When students experience negative emotions such as frustration, confusion, or disengagement, their ability to learn effectively decreases. Conversely, positive emotions like curiosity and confidence enhance their understanding and participation. Therefore, understanding and monitoring student emotions can provide valuable insights into their learning behavior and help educators adapt teaching strategies accordingly. The proposed methodology focuses on implementing an emotion detection system using advanced AI-based techniques. This system aims to monitor students' emotional states during online classes by analyzing facial expressions and other behavioral cues. By identifying emotions such as happiness, boredom, confusion, or stress in real time, the system can assist mentors in providing timely feedback and support, thereby improving student engagement and academic performance. In the current educational landscape,

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the need for such systems has become more relevant than ever. The post pandemic shift to remote learning environments has highlighted the limitations of existing online education models in maintaining emotional connection and personalized guidance. Implementing emotion detection not only bridges this gap but also opens pathways for emotion-aware learning platforms that enhance the overall quality of education. Moreover, this approach aligns with the global trend of utilizing AI for human-centered learning analytics, making it a significant step toward the future of intelligent education systems.

2. Related Works and Background

With the rise of digital learning, maintaining student engagement and emotional awareness has become a growing challenge. To address this, researchers have explored artificial intelligence, computer vision, and deep learning techniques to automatically recognize and interpret emotions. Among these, facial-expression-based emotion recognition has emerged as a key approach for assessing learner engagement in real time. This section reviews major studies contributing to this field and their applications in improving online learning experiences. Avital et al. [1] developed a classroom-based emotion recognition system capable of identifying students' emotions in real time during lectures. The system employed a Convolutional Neural Network (CNN) alongside the Viola–Jones face detection algorithm to capture and classify facial expressions. Tested with 45 students, the model achieved an 83% accuracy rate, which closely aligned (91.7%) with self-reported emotions. The authors also suggested that future versions could be accelerated using photonic neural networks. This research demonstrates how real-time facial expression analysis can enhance teaching by helping instructors adapt to students' emotional states dynamically. Kale [2] explored speech-based emotion recognition systems aimed at advancing Human–Machine Interaction (HMI). Although unrelated to facial recognition, this study holds strong relevance for educational contexts, particularly for children. Various algorithms, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forests, were compared using audio-based features such as pitch and tone to classify emotions. The findings revealed that children's speech poses challenges due to variability in articulation, pronunciation, and tone. Kale's research highlights the broader complexity of capturing emotional cues accurately, which parallels similar issues faced in visual emotion recognition systems. Malka et al. [3] designed a multimodal system to detect students' alertness and emotional states in online learning environments. Their approach combined eye tracking, facial landmarks, and posture detection as inputs for machine learning algorithms. The system automatically generated alerts for instructors when students appeared disengaged, enabling adaptive teaching interventions. The authors reported that the multimodal framework achieved superior accuracy compared to single-modality systems. This work supports the concept of integrating real-time emotional monitoring to improve engagement in digital classrooms. Hinojosa Lee et al. [4] investigated performance metrics in multilabel emotion classification systems by comparing micro, macro, and weighted F1-scores. Their study offered insights into selecting appropriate evaluation metrics for emotion recognition models, emphasizing that traditional accuracy measures can misrepresent model performance in imbalanced datasets. The research provided a methodological foundation for future emotion detection studies, especially those applied in educational or affective computing systems where multiple emotions coexist. Wu [5] proposed a real-time facial expression recognition model tailored for online lectures to monitor students' emotional engagement. The system utilized advanced image processing and classification techniques to capture facial changes through webcams, providing instructors with real-time visual feedback on student attention. The model's high detection accuracy demonstrated the potential of facial emotion analysis for improving remote learning environments and understanding learner behavior dynamically. Mart´ınez and Vega [6] developed a ROS-based facial emotion detection system integrated with a low-cost robot using Raspberry Pi. Their approach employed traditional machine learning classifiers in combination with OpenCV-based facial feature extraction to recognize

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emotions in real time. The system was optimized for embedded environments, making it efficient and affordable for educational and interactive robotics applications. This study illustrates how emotion detection can extend beyond virtual platforms to physical classroom assistants, thereby enhancing student engagement and interaction through human-like responses. Boudouri and Bohi [7] introduced EmoNeXt, an adapted ConvNeXt model for facial emotion recognition. The authors enhanced the baseline ConvNeXt architecture to improve both feature extraction and emotion classification accuracy across multiple datasets. Their method achieved superior results in recognizing subtle facial expressions by utilizing optimized transfer learning techniques and fine-tuned convolutional layers. This contribution highlights the growing effectiveness of advanced deep learning models in emotion recognition, offering scalable frameworks for real-time educational applications. Roy et al. [8] presented ResEmoteNet, a hybrid deep learning architecture designed to balance accuracy and loss reduction in facial emotion recognition. Their framework incorporated residual learning and dropout optimization to minimize overfitting while preserving model robustness. The study demonstrated significant performance gains over conventional CNNs, particularly in datasets with varied lighting and pose conditions. ResEmoteNet establishes a strong basis for emotion-aware e-learning systems that require stable and efficient emotion recognition under real-world conditions. Wang et al. [9] designed an Affective Emotional Learning Tutoring System for mobile devices to support adaptive and personalized learning. Their system integrated affective feedback and emotion recognition to tailor instructional content based on students' emotional states. Usability tests confirmed the system's effectiveness in improving learner satisfaction and engagement. The research emphasized that mobile learning platforms benefit greatly from affective computing components, paving the way for emotion-adaptive educational technologies. Quiroz-Mart´ınez et al. [10] developed a real-time emotion recognition system to analyze students' emotions during live classroom sessions. The system used video data to detect emotional patterns such as confusion, interest, and frustration, enabling instructors to make timely pedagogical adjustments. Their implementation demonstrated how emotion analysis could bridge the gap between traditional and technology assisted teaching by offering objective insights into student behavior. This work underscores the importance of emotional analytics in enhancing both teaching efficiency and learning experiences. Shukla et al. [11] proposed a facial emotion recognition model combining Deep Convolutional Neural Networks (CNN) with the HAAR Cascade algorithm for efficient face detection and classification. The integration of HAAR features allowed quick localization of facial regions, while the CNN ensured accurate recognition of emotional expressions. Their model achieved impressive performance across standard datasets, showing particular robustness against lighting variations and occlusions. This hybrid approach demonstrates how classical and deep learning methods can complement each other in real-time educational applications. Wang et al. [12] developed an online classroom engagement analysis framework based on facial expression recognition using an enhanced YOLOv5 model. Their system aimed to mitigate issues such as cyberbullying and lack of participation in virtual classrooms. By detecting engagement levels through facial emotions, the model offered real-time insights into students' attention and mood. The enhanced YOLOv5 architecture ensured high-speed processing with strong detection precision, emphasizing the potential of emotion-aware surveillance for maintaining positive learning environments. Shomoye and Zhao [13] introduced an automated emotion recognition system for students in virtual reality (VR) classrooms. Their model captured facial expressions and behavioral cues from VR interactions to identify emotional states such as confusion, engagement, and frustration. The results demonstrated the feasibility of integrating emotion recognition into immersive learning spaces, where traditional cameras may be ineffective. The authors highlighted how emotional analysis in VR could enhance personalized feedback and adaptive learning in next-generation educational platforms. Das and

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Dev [14] explored methods to optimize student engagement detection through the integration of facial and behavioral features. Their study combined computer vision techniques with machine learning classifiers to evaluate engagement based on head posture, eye gaze, and emotional cues. The proposed model improved accuracy in detecting disengagement compared to emotion-only models. Their findings underline the importance of multimodal feature fusion in developing robust systems for evaluating learner participation. Tahri and Arfaoui [15] proposed a deep learning-based facial emotion recognition model specifically designed for elearning environments. Their framework utilized CNN architectures to automatically extract relevant emotional features from facial data, addressing challenges related to varying illumination and head orientation. The authors demonstrated that their model could effectively distinguish between multiple emotional states in online settings, making it a suitable tool for enhancing real-time learning assessment systems. Sharma et al. [16] designed a student engagement detection system incorporating emotion analysis, eye tracking, and head movement monitoring. Their model applied multiple machine learning techniques to predict engagement levels based on combined behavioral and affective cues. The approach achieved high reliability across test sessions, proving the advantage of multimodal analysis for understanding learner behavior. This work serves as a significant step toward developing adaptive educational tools capable of responding to students' attention patterns dynamically. Bahreini et al. [17] developed a real-time speech emotion recognition system for affective e-learning applications. Their research emphasized the role of vocal cues—such as tone, pitch, and rhythm—in identifying learner emotions. The system aimed to support adaptive tutoring environments that respond to emotional changes in students' speech during lessons. The study's contribution lies in extending emotion recognition beyond visual signals, reinforcing the value of multimodal emotional data in personalized e-learning systems. Wang et al. [18] introduced an affective tutoring system for mobile devices integrating emotional state monitoring and adaptive learning mechanisms. The system captured learners' emotional reactions through facial analysis and adjusted educational content accordingly. User evaluations indicated enhanced motivation and learning outcomes when emotional feedback was included. The study validated the practical benefits of affect-aware mobile tutoring systems for individualized learning support. Zhou et al. [19] developed a deep learning-based model for real-time emotion recognition from video streams. The system utilized CNN and LSTM layers to process temporal and spatial features of facial expressions, enabling continuous emotion monitoring during live sessions. Their model achieved strong accuracy across different lighting and background conditions, demonstrating applicability in both classroom and remote learning scenarios. The research provided valuable insights into integrating real-time video analytics for emotion-aware education systems. Gupta et al. [20] designed a deep learning–based framework for real-time learner engagement detection in online learning environments. Their system employed facial emotion recognition to measure engagement levels, identifying moments of distraction or disinterest. The integration of CNN and other deep models allowed for high precision and adaptability to different student demographics. This study's findings highlight the growing significance of combining emotion recognition and engagement analytics to create interactive and responsive educational technologies.

3. Methodology

The proposed system is designed to detect students' emotions in real time during online classes, providing both immediate alerts for mentors and long-term insights through timeline analysis. The methodology consists of the following stages:

3.1. Dataset

Good fellow et al. [21] introduced the FER-2013 (Facial Expression Recognition 2013) dataset, one of the most widely used benchmarks for facial emotion recognition, during the ICML 2013 Challenges in Representation Learning. The dataset was introduced during the ICML 2013 Challenges in Representation Learning and contains a total of 35,887 grayscale images, each sized 48×48 pixels and collected from

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internet sources such as Google image searches. The dataset is categorized into seven emotion classes with the following distribution: Angry (4,953 images), Disgust (547 images), Fear (5,121 images), Happy (8,989 images), Sad (6,077 images), Surprise (4,002 images), and Neutral (6,198 images). To ensure robust training and evaluation, the dataset is divided into three official splits: training set (28,709 images), public test set (3,589 images), and private test set (3,589 images). Each image in the dataset contains a face in varied real-world conditions, including differences in lighting, pose, and occlusion, making it a challenging yet effective resource for deep learning–based emotion recognition. FER-2013 is freely available on Kaggle, and its combination of diversity and difficulty makes it ideal for developing models that generalize well to unseen data.

Figure 1 Sample images from the FER-2013 dataset representing seven emotion classes

3.2. Preprocessing

The raw video stream is processed using OpenCV. Face detection is performed using Haar Cascade Classifiers to isolate facial regions. Each detected face is resized and normalized to maintain consistency in input dimensions, which improves model stability and accuracy.

3.3. Feature Extraction and Classification

A Convolutional Neural Network (CNN) is employed for emotion recognition. The CNN architecture automatically learns hierarchical features from facial regions. Convolutional and pooling layers extract spatial features, while fully connected layers classify emotions into the corresponding categories. The trained model predicts the student's emotional state frame by frame, ensuring continuous monitoring during the session. These detected emotions are simultaneously displayed on the mentor's interface in real time, allowing continuous observation of student engagement. When negative emotions such as fear, anger, or sadness persist beyond a defined threshold, the decision module triggers an alert to notify the mentor for timely intervention.

3.4. Alert Mechanism

IIf the system detects prolonged negative emotional states such as sadness, fear, or anger, an alert is automatically generated and sent to the mentor in real time. The decision module continuously tracks emotional patterns across frames, and when a specific negative emotion persists beyond a defined time threshold, it flags that instance as a potential disengagement or emotional distress. This automated alert is displayed on the mentor's dashboard along with the student's live video feed, enabling the educator to identify who requires attention. By receiving these real-time notifications, mentors can take immediate corrective action—such as modifying their teaching approach, offering encouragement, or initiating interaction with the affected student. This proactive feedback mechanism helps maintain student focus and emotional well-being, ensuring that learning remains interactive and empathetic. Over time, the alert history also contributes to emotion trend analysis, providing valuable insights into recurring engagement challenges or emotional patterns among learners.

3.5. Emotion Timeline Analysis

Alongside real-time alerts, the system generates a timeline of emotional variations throughout the session. This timeline is visualized as a graph, helping mentors analyze patterns such as periods of disengagement or spikes in confusion. These insights provide valuable post-session feedback for

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instructional improvement.

3.6. Mentor Feedback Integration

The combination of real-time alerts and timeline-based insights creates a feedback loop. Educators can use this feedback to refine teaching strategies, design more engaging content, and better support students in virtual learning environments.

3.7. System Flow

The overall workflow of the methodology is illustrated in Figure 1, which shows the pipeline from webcam input through preprocessing, CNN classification, alert generation, and timeline visualization leading to mentor feedback.

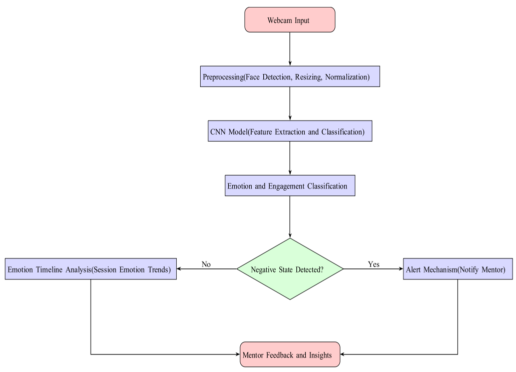

Figure 2 System Flow of the Proposed Emotion and Engagement Monitoring Methodology

4. Detailed Methodology

The proposed real-time emotion and engagement monitoring system aims to detect and display students' emotional states continuously during online learning. The system consists of five main modules: input acquisition, preprocessing, CNN-based feature extraction and classification, live emotion display, and decision and feedback generation. Each module works in a pipeline to ensure smooth and low-latency operation throughout the session. The process begins with the webcam input module, which captures live video frames of students. These frames are passed to the preprocessing module, where facial regions are detected using the Haar Cascade Classifier. The detected faces are cropped, converted to grayscale, normalized, and resized to 48×48 pixels to match the FER-2013 dataset format. Additional enhancement steps, such as noise reduction and histogram equalization, are applied to improve detection quality and ensure consistent input for the model. The preprocessed facial images are then forwarded to the CNN-based feature extraction and classification module. The CNN model automatically learns spatial features from facial regions and classifies them into one of seven emotion categories: happy, sad, angry, surprised, fearful, disgusted, or neutral Shown in Figure 2. The architecture consists of multiple convolutional and pooling layers for feature learning, dropout layers for regularization, and fully connected dense layers for classification. The final softmax layer provides emotion probabilities for each frame, enabling real-time recognition. The detected emotion labels are immediately displayed above each student's face in the live video feed, providing a continuous and transparent view of emotional states during the session. The predicted emotions are then analyzed in the decision and alert module, which tracks emotional trends over time. If a negative emotion such as boredom or frustration persists for a set duration, the system triggers an alert to notify the mentor. Simultaneously, the mentor feedback interface visualizes live labeled video streams and emotion timelines, allowing instructors to observe engagement trends and respond appropriately. A continuous feedback loop connects the mentor interface back to the input stage, ensuring uninterrupted realtime monitoring. Overall, this architecture combines efficient CNN-based emotion recognition with continuous visualization and timely alerting, creating a responsive and emotionally aware online learning environment.

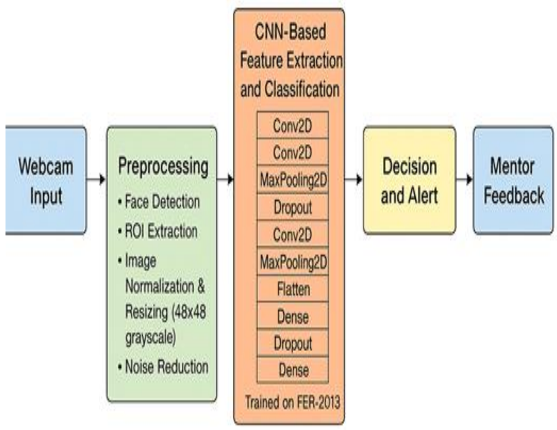

Figure 3 System architecture of the proposed real-time emotion detection model

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The proposed system architecture provides a practical and intelligent way to understand students' emotions during online learning. By combining real-time facial analysis through a CNN model with decision and feedback mechanisms, the system helps mentors stay aware of students' emotional states and respond at the right time Shown in Figure 3. Its modular design not only ensures smooth and accurate performance but also allows flexibility for future improvements, such as adding voice or posture analysis. Overall, this architecture supports a more connected, empathetic, and effective virtual learning experience for both students and teachers.

Conclusion

To sum up, with the rise of online learning, understanding how students feel during virtual classes has become a real challenge. Unlike traditional classrooms where teachers can easily read facial expressions and adjust their teaching, virtual settings often miss these important cues. That's where facial emotion recognition comes in—by using advanced computer vision and deep learning techniques like CNNs and HAAR Cascades, we can now detect and interpret students' emotions in real time through their webcams. This technology not only helps identify feelings such as boredom, confusion, or frustration but also supports teachers by sending timely alerts when students struggle emotionally. Visualizing emotion patterns throughout a class can give educators valuable insights to improve engagement and personalize learning. Bringing emotional awareness into digital classrooms like this has the potential to make online education more responsive, empathetic, and effective. As research and technology continue to improve, these systems will be key to bridging the emotional gap in virtual learning and creating a richer, more connected educational experience for everyone involved.

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