AI- Based Student Engagement Detection using CNN, CBAM, and TCN

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Abstract
Online learning has emerged as a transform--ative trend in modern education due to its flexibility, accessibility, and ability to deliver personalized learning experiences. However, evaluating student engagement in virtual environments remains a significant challenge, as traditional assessment approaches primarily rely on synchronous, face-to-face interaction, which is often limited or absent in online settings. To address this issue, this paper proposes a novel framework for automated student engagement detection using facial emotion recognition techniques. The proposed system integrates a hybrid deep learning architecture that combines Convolutional Neural Networks (CNN), Convolutional Block Attention Module (CBAM), and Temporal Convolutional Networks (TCN) to effectively capture both spatial and temporal characteris--tics of facial expressions. CNN is utilized to extract robust spatial features from facial images, while CBAM enhances feature representation by emphasizing salient spatial and channel-wise information. Furthermore, TCN models sequential emotional variations across video frames, enabling comprehensive analysis of dynamic engagement patterns. To support the development and evaluation of the model, a specialized dataset was constructed to capture diverse engagement scenarios in realistic online learning environments. Experimental results demonstrate that the proposed system achieves a classification accuracy of 92.3%, outperforming baseline CNN models and ensuring reliable real-time performance. The framework provides actionable insights for educators and establishes a scalable, intelligent solution for enhancing engagement analytics in virtual education systems.

Keywords:
Convolutional Neural Networks (CNN); Convolutional Block Attention Module (CBAM); Temporal Convolutional Networks (TCN); Facial Emotion Recognition (FER); Student Engagement.

I .Introduction

1.1 Background

The rapid growth of online education has created challenges in monitoring student engagement. Unlike traditional classrooms, virtual environments lack direct visual cues that help instructors assess student attention and participation. This study addresses the issue using automated facial emotion recognition technology.

1.2 Problem Statement

Current online learning platforms provide limited feedback on student engagement, resulting in decreased learning outcomes, higher dropout rates, reduced instructor–student interaction, and difficulty identifying struggling learners.

1.3 Proposed Solution

This paper proposes a deep learning–based system for real-time student engagement detection in online environments. The system captures facial expressions through webcam feeds, analyzes emotions using CNN-based models, evaluates temporal engagement patterns, and provides real-time feedback to instructors to improve teaching effectiveness and learning outcomes.

II. Literature Review

2.1.CNN with Attention for Facial Emotion Recognition

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Recent studies show that combining CNN with attention mechanisms improves facial emotion Aly (2024) proposed a deep learning framework integrating ResNet-50, CBAM, and Temporal Convolutional Networks (TCN) to capture spatial and temporal features. The model achieved higher accuracy on datasets such as RAF-DB, FER2013, and CK+ compared to standard CNN models. The study highlights the importance of attention modules in improving dynamic engagement detection.

Similarly, Miskow and Altahhan (2024) evaluated CBAM with CNN backbones and found that attention-augmented models significantly improved emotion classification accuracy by focusing on important facial regions.

recognition (FER) performance.

2.2 Temporal Modeling in Emotion Recognition

Temporal modeling plays a crucial role in video-based FER.

Zhou et al. (2024) integrated TCN with deep learning models to capture temporal dependencies in emotional sequences, demonstrating improved continuous emotion recognition performance.

Savchenko and Sidorova (2024) combined CNN (EfficientNet) with TCN for video-based FER and showed that temporal modeling significantly enhanced classification accuracy.

Mehta and Yang (2023) proposed NAC-TCN, an attention-based TCN variant, which maintained causal temporal relationships and achieved competitive performance compared to traditional RNN and TCN models.

Summary of Trends

Model Type	Key Value	Applicability
CNN + CBAM	Enhances spatial focus on relevant facial regions	Static frame emotion classification
CNN + TCN	Captures temporal evolution of expressions	Video-based or continuous FER
Hybrid CNN-Attention-TCN	Combines spatial attention + temporal dynamics	Engagement tracking in real-time online learning

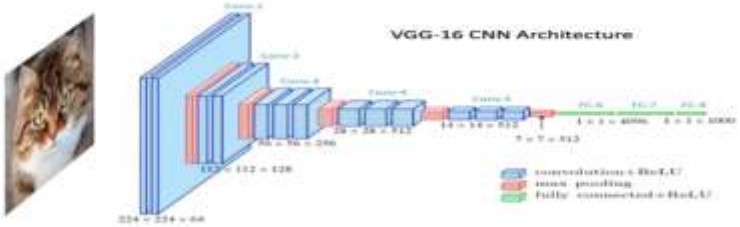
III .Methodology

3.1 Convolutional Neural Network (CNN)

Facial Emotion Recognition (FER) using CNN is a deep learning approach used to automatically detect human emotions from facial images. Popular datasets such as FER-2013, CK+, and RAF-DB are commonly used for training and evaluation.

The process begins with data preprocessing, including face detection, resizing images to a fixed size, normalization, and data augmentation (rotation, flipping, brightness adjustment). These steps improve model robustness and reduce overfitting.

CNN consists of convolution layers that extract spatial features such as edges, textures, and facial components (eyes, mouth, eyebrows). ReLU activation introduces non-linearity, and pooling layers reduce dimensionality. Finally, fully connected layers and a Softmax function classify emotions into categories such as happy, sad, angry, surprise, and neutral.



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3.2 Convolutional Block Attention Module (CBAM)

CBAM is a lightweight attention mechanism that improves CNN performance by focusing on important features. It applies two types of attention:

- Channel Attention (CAM): Identifies which feature channels are important using global average and max pooling.
- Spatial Attention (SAM): Identifies important facial regions (eyes, mouth, eyebrows).

CBAM is inserted into the CNN backbone (e.g., ResNet-50, VGG, MobileNetV2) to refinefeatures.

Pipeline:

Input Image → CNN → CBAM → Fully Connected Layer → Softmax

CBAM improves accuracy by emphasizing emotion-relevant facial regions while suppressing irrelevant information.

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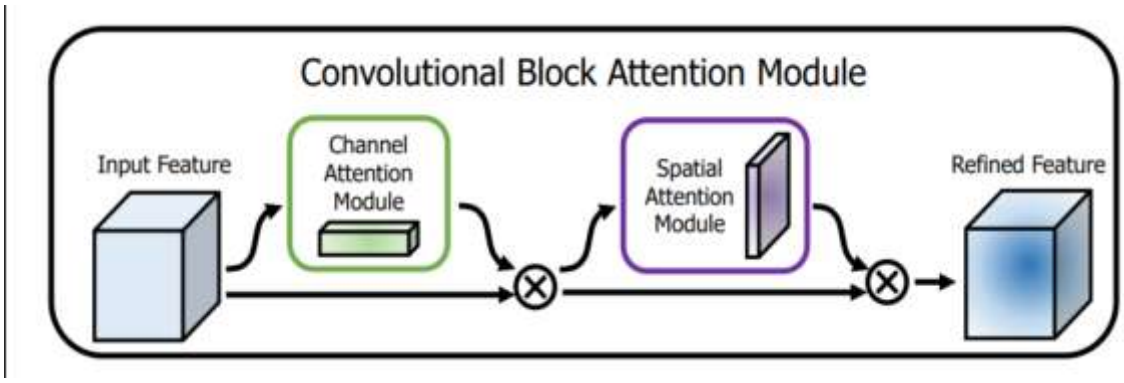

3.3.Temporal Convolutional Network (TCN)

TCN is used to model temporal patterns in video-based facial expressions. Unlike RNNs or LSTMs, TCN uses convolution operations while maintaining sequence order.

Key components include:

- Causal Convolution: Ensures predictions depend only on past and current frames.
- Dilated Convolution: Expands the receptive field to capture long-term dependencies.
- Residual Connections: Improve gradient flow and stabilize deep networks.

TCN effectively models emotional changes over time, making it suitable for engagement detection in online classes.

3.4. Proposed Framework

The proposed system works as follows:

1. Frame-LevelFeatureExtraction
   CNN extracts spatial features from each videoframe.
   CBAM refines important facial regions.
2. SequenceFormation
   Consecutive frame features are stacked into sequences.
3. TemporalModeling
   TCN analyzes emotional evolution over time.
4. Classification
   Fully connected layer with Softmax predicts engagement level.

Pipeline:

Input Video → CNN + CBAM → Feature Sequence → TCN → Classification

3.5.Data Preprocessing

- Dataset collection from online classroom webcam feeds
- Manual annotation of emotion labels
- Image resizing and normalization
- Histogram equalization for lighting correction

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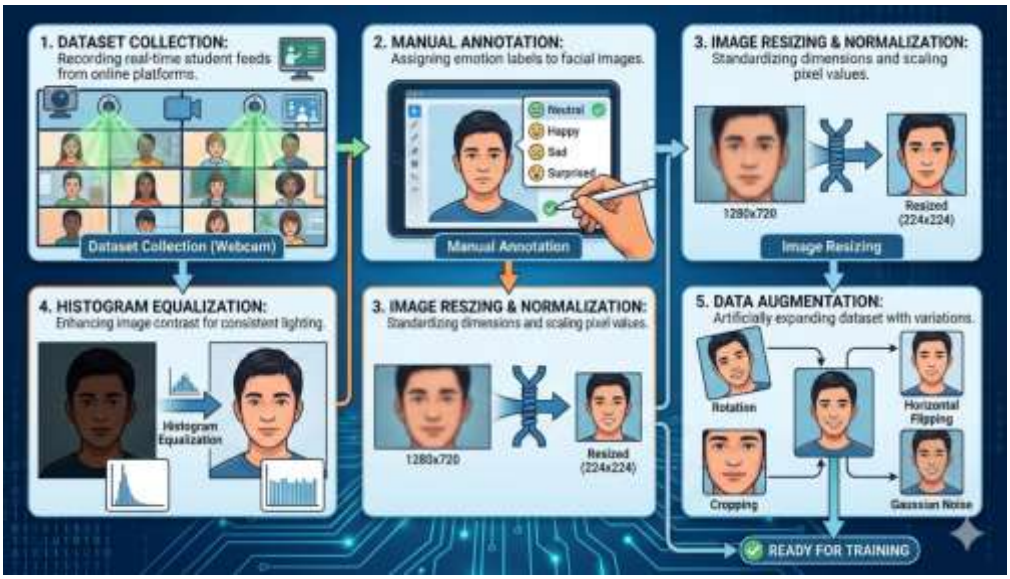
- Data augmentation (rotation, flipping, cropping)



3.6.Training Strategy

Model performance depends on:

- Optimizer selection
- Learning rate scheduling
- Batch size and epochs
- Early stopping

Regularization techniques prevent overfitting and improve generalization.

IV .Challenges

Facial emotion recognition in online learning environments faces several significant challenges. Variations in lighting conditions and differences in camera quality can greatly affect image clarity, leading to inconsistent feature extraction and reduced model accuracy. Additionally, occlusions caused by hands, masks, spectacles, or partial face visibility, along with frequent head movements, can distort facial features and make emotion detection more difficult. Another major challenge lies in recognizing subtle emotional expressions, as minor facial muscle changes may not be easily distinguishable, especially in low-resolution video streams. The computational requirements of deep learning models such as CNN, CBAM, and TCN also pose limitations, as real-time engagement detection demands sufficient processing power and memory resources. Furthermore, the development of robust models requires large, well-annotated datasets representing diverse demographics, lighting conditions, and expression intensities, which can be time-consuming and expensive to collect. Addressing these challenges is essential for building a reliable and scalable engagement detection system for online

V.Future Enhancment

Extend the system into a **multimodal engagement detection framework** for more comprehensive analysis.

Integrate **eye gaze tracking** to monitor visual attention, focus levels, and screen interaction behavior.

Incorporate **speech emotion recognition** to analyze vocal tone, pitch, and intensity for detecting confusion, interest, or frustration.

Implement **gesture and posture analysis** to interpret body language cues such as head movements, leaning posture, and hand gestures.

Combine facial, vocal, and behavioral signals to build a more robust and context-aware engagement assessment model.

- Integrate the system with **Learning Management Systems (LMS)** such as Moodle or Google Classroom.
- Enable **real-time analytics dashboards** for instructors.

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Provide **automated reports and personalized feedback** for students.

Support **adaptive content delivery** based on engagement levels.

VI .Conclusion

This study proposed an intelligent student engagement detection framework based on facial emotion recognition enhanced through advanced deep learning techniques. The model utilizes Convolutional Neural Networks (CNN) for effective spatial feature extraction and integrates the Convolutional Block Attention Module (CBAM) to emphasize discriminative facial regions associated with emotional expressions. By incorporating Temporal Convolutional Networks (TCN), the system captures temporal dependencies in emotional progression across video frames, enabling dynamic behavioral analysis rather than relying solely on static image-based predictions.

The combination of spatial attention and temporal modeling significantly improves engagement classification performance by enhancing feature discrimination, increasing robustness to noise and environmental variations, and improving sensitivity to subtle emotional transitions. The proposed architecture is computationally efficient and scalable, making it suitable for real-time deployment in online learning environments.

Overall, the integration of deep learning–based facial emotion recognition with temporal sequence modeling presents a promising approach for automated student engagement assessment. The framework establishes a strong foundation for future multimodal enhancements and practical implementation within modern digital education platforms

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