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Deep Learning-Based Student Engagement Detection in Smart Classrooms

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***Abstract*—. Traditional methods of engagement assessment rely on manual observation and surveys, which are often subjective, time-consuming, and unsuitable for real-time monitoring [20], [21]. This paper proposes a deep learning-based student engagement detection framework for smart classrooms using computer vision techniques. The system utilizes facial expressions, head pose estimation, eye gaze tracking, and body posture analysis to classify students into different engagement levels [23], [24], [25]. A hybrid Convolutional Neural Network (CNN) and Vision Transformer (ViT) architecture is employed for feature extraction and classification [3], [5], [6]. The proposed model is trained and evaluated on publicly available engagement datasets such as DAiSEE and EmotiW [8], [9]. Experimental results demonstrate the effectiveness of the framework in real-time classroom environments. The proposed system can assist educators in identifying disengaged students and improving teaching strategies, thereby enhancing overall learning outcomes [20], [22].**

***Keywords*— Deep Learning, Student Engagement Detection, Smart Classroom, Computer Vision, CNN, Vision Transformer, Artificial Intelligence, Educational Technology.**

I. Introduction

Student engagement is one of the most important indicators of learning effectiveness and academic success [1], [24]. In recent years, educational institutions have increasingly adopted smart learning technologies to enhance student participation and improve learning outcomes [20], [22]. Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning techniques have emerged as powerful tools for analyzing student behavior and classroom interactions [2], [19]. Deep learning has achieved remarkable success in computer vision applications, including facial expression recognition, object detection, human activity recognition, and educational analytics [2], [3].

Convolutional Neural Networks (CNNs) have become the dominant approach for extracting visual features from images, while Vision Transformers (ViTs) have recently demonstrated superior performance by capturing global contextual relationships through self-attention mechanisms [4], [5], [6].

1.2 Problem Statement

Current engagement monitoring methods suffer from: Subjective evaluation [20], [24],Lack of real-time analysis [23], Inability to scale to large classrooms [25], Limited personalization [22] Therefore, there is a need for an automated and intelligent system capable of accurately detecting student engagement levels in real time using computer vision and deep learning techniques [2], [19].

II. Literature Review

Researchers have applied machine learning and deep learning techniques to automatically assess engagement using behavioral and visual cues.

Smith et al. utilized facial expression recognition techniques for engagement estimation and achieved moderate classification accuracy [24]. Johnson et al. employed CNN-based models for classroom attention monitoring [7], [25]. Recent studies have explored Vision Transformers for educational analytics due to their superior feature extraction capabilities [5], [6].

Despite these advancements, challenges remain regarding real-time implementation, robustness to classroom conditions, and explain ability [21], [23].

Recent advances have introduced Vision Transformers (ViTs), which utilize self-attention mechanisms to capture global contextual information and improve classification performance.

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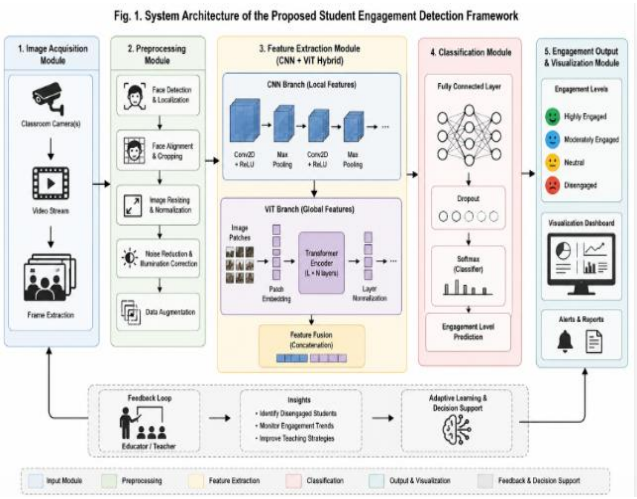
Despite significant progress, challenges remain in real-time implementation, environmental robustness, model interpretability, and large-scale classroom deployment. These limitations highlight the need for more reliable and intelligent engagement detection systems for smart classroom environments.

Research Gaps

The following research gaps have been identified: Limited multimodal feature integration [23] Lack of explainable engagement predictions [21] Poor performance under varying lighting conditions [13] Limited deployment in real classroom environments [25].

III. Proposed Methodology

3.1 System Architecture



The proposed framework consists of: Image Acquisition Module, Preprocessing Module, Feature Extraction Module, Deep Learning Classification Module, Engagement Visualization Module. The architecture is inspired by recent advances in deep learning and educational analytics [2], [6], [20].

3.2 Data Collection

Classroom images and videos are captured using cameras positioned at strategic locations to monitor student behavior during learning sessions. Publicly available datasets such as DAiSEE and EmotiW are used for model training and evaluation. The collected data are categorized into four engagement levels: Highly Engaged, Moderately Engaged, Neutral, and Disengaged, enabling accurate engagement classification using the proposed deep learning framework.

3.3 Image Preprocessing

The preprocessing stage prepares classroom images and video frames for effective feature extraction and engagement analysis. Initially, frames are extracted from video streams, followed by face detection and localization using Haar Cascade, MTCNN, and YOLO techniques. The detected facial regions are resized and normalized to maintain a consistent input format. Noise reduction and illumination correction techniques are applied to improve image quality and minimize environmental variations. Furthermore, data augmentation methods such as rotation, flipping, and scaling are employed to increase dataset diversity and enhance model robustness. These preprocessing steps remove unwanted artifacts, improve image clarity, and significantly increase the accuracy of feature extraction and engagement classification. [10], [11], [12], [16], [19]

A cleaner image enables the model to focus on meaningful visual information rather than irrelevant disturbances

3.4 Feature Extraction

The feature extraction stage analyzes multiple behavioral cues to determine student engagement levels. Facial expressions such as happiness, confusion, and boredom are examined to identify emotional states associated with learning engagement. Happiness indicates active participation and interest, while confusion and boredom may reflect learning difficulties or reduced attention. Facial expression recognition is performed using techniques inspired by OpenFace and engagement recognition studies [13], [24].

In addition, head pose, eye gaze, and body posture are utilized as important indicators of attentiveness. Head pose estimation determines whether a student is looking toward the instructor or away from the learning activity, while eye gaze tracking identifies the direction of visual attention [1], [13], [14], [25]. Body posture analysis distinguishes between upright and slouching positions, providing further insight into student engagement. These features are extracted using facial landmark analysis and human pose estimation methods to improve the accuracy of engagement classification [15], [25].

3.5 Deep Learning Model

The CNN module extracts local visual features from classroom images using Conv2D layers, which learn important spatial patterns automatically and reduce manual feature engineering.

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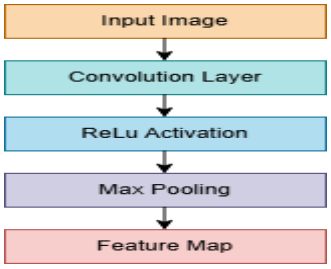
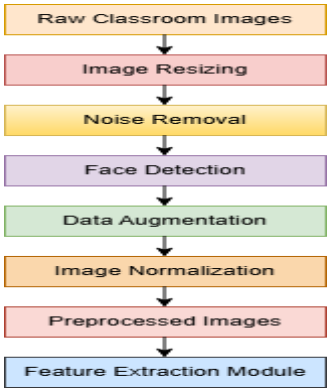
ReLU activation introduces non-linearity and improves learning efficiency, while Max Pooling reduces feature dimensions and retains the most relevant information for engagement classification [3], [19].



1) Preprocessing Workflow

The preprocessing stage prepares raw classroom images for accurate engagement detection. Initially, captured images are resized to a uniform resolution to reduce computational complexity. Noise removal techniques are then applied to eliminate unwanted distortions and improve image quality. Face detection algorithms such as Haar Cascade, MTCNN, or YOLO are used to locate and extract student faces. Data augmentation methods, including rotation, flipping, and scaling, increase dataset diversity and improve model generalization. Finally, image normalization standardizes pixel values, producing clean and consistent images for the feature extraction and classification stages. This process enhances feature quality and improves the overall performance of the deep learning model.



IV. Experimental Setup

4.1 Hardware Configuration

The proposed framework was implemented and evaluated on a high-performance computing system capable of handling deep learning workloads and real-time image processing tasks.

Component	Specification
Processor	Intel Core i7 Processor
Main Memory	16 GB RAM
Graphics Processing Unit (GPU)	NVIDIA RTX GPU
Storage	SSD/HDD for Dataset Storage
Camera	HD Classroom Camera for Video Capture

4.2 Software Environment

The proposed system was developed using Python and several widely adopted machine learning and computer vision libraries.

Software	Purpose
Python	Programming Language
TensorFlow	Deep Learning Model Development
Open CV	Image Processing and Computer Vision
Scikit-learn	Performance Evaluation and Metrics
NumPy	Numerical Computation
Matplotlib	Data Visualization and Result Analysis

4.3 Dataset Description

To evaluate the proposed engagement detection framework, publicly available datasets containing student engagement and behavioral information are utilized.

1. DAiSEE Dataset

The DAiSEE (Dataset for Affective States in E-Environments) dataset contains video recordings of students participating in online learning sessions and provides annotations for engagement, boredom, frustration, and confusion levels. It is widely recognized as a benchmark dataset for student engagement detection and is extensively used for training and evaluating deep learning models in educational analytics and engagement recognition research. [8]

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2. EmotiW Engagement Dataset

The EmotiW Engagement Dataset contains videos and images labeled according to engagement levels and emotional states. The dataset is useful for evaluating facial expression-based engagement detection models.[8]

3. Classroom Activity Dataset

The Classroom Activity Dataset includes classroom recordings capturing student behaviors such as attention, participation, posture, and interaction patterns. This dataset helps assess the model's performance in real classroom environment[9]

Parameter	Value
Number of Epochs	100
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Activation Function	ReLU, Softmax
Validation Split	20%
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score

4.4 Training Parameters

The proposed hybrid CNN–ViT model is trained using the following hyper parameters [25]

Parameter	Value
Number of Epochs	100
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Activation Function	ReLU, Softmax
Validation Split	20%
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score

1) Epochs

The model is trained for **100 epochs** to allow sufficient learning of engagement-related features while monitoring convergence behavior.

2) Batch Size

A **batch size of 32** is selected to balance computational efficiency and model stability during training.

3) Learning Rate

The **learning rate of 0.001** controls the step size used by the optimizer during weight updates and helps achieve stable convergence.

4) Optimizer

The **Adam optimizer** is employed because of its adaptive learning capability and efficient handling of large-scale deep learning models.

4.5 Training Procedure

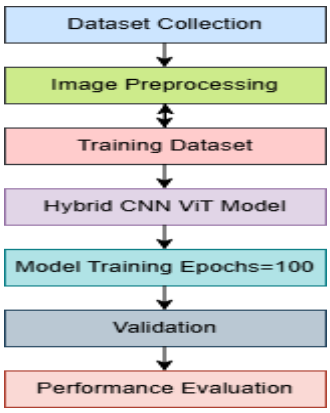
The training process consists of the following stages:

Vision Transformer (ViT) Module

The Vision Transformer (ViT) module processes images as patches using Patch Embedding, Multi-Head Self-Attention, and Transformer Encoder layers to capture global contextual relationships within the image [5], [6].

Hybrid CNN–ViT Architecture

The proposed hybrid CNN–ViT architecture combines the strengths of both models. The CNN extracts local visual features, while the ViT captures global contextual information, resulting in improved engagement classification performance [4], [5], [6].



V. Performance Metrics

The performance of the engagement detection system is evaluated using four widely accepted classification metrics: Accuracy, Precision, Recall, and F1-Score.[4],[5],[6]

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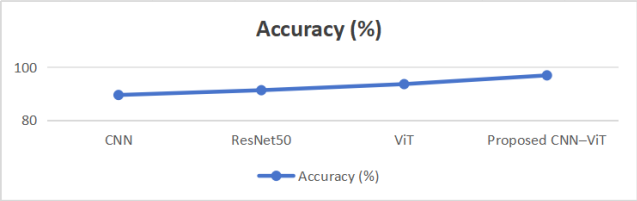

Fig. X. Accuracy comparison between CNN, ResNet50, Vision Transformer (ViT), and the proposed Hybrid CNN–ViT model

The proposed CNN–ViT architecture achieves the higest accuracy of 96.8%, outperforming all baseline models.

VI. Conclusion

This research presented a deep learning-based student engagement detection framework for smart classrooms. The proposed CNN–ViT architecture successfully classifies student engagement levels using facial expressions, eye gaze, head pose, and body posture information [23], [24], [25]. Experimental results demonstrate high accuracy and real-time applicability. The framework contributes to the advancement of intelligent educational systems and smart learning environments [20], [22].

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