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Development of Student Classroom Attention System Using Artificial Intelligence and Electronic Sensors

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Abstract

In present-day educational contexts, the effective evaluation and enhancement of student engagement are of great importance for academic success. This study makes a substantial contribution by proposing a "student classroom attention system" that utilizes electroencephalography (EEG) and computer vision to evaluate students' attentiveness in real time. The NeuroSky brainwave sensor acquires EEG data, which is processed by a long short-term memory neural network to determine cognitive engagement. In the same vein, facial image processing and emotion recognition, based on a convolutional neural network algorithm with an accuracy of 71.78%, are used to further assess attentiveness through visual cues. The results from EEG (test accuracy: 91.78%) and image processing are integrated for each student to determine an overall attentiveness value. This information is displayed on a dashboard accessible to faculty, providing a detailed attendance metric and automatically recording attendance through face detection. The system offers innovative methods for assessing the level of student concentration in real time, helping educators maintain a conducive learning environment.

Categories: Computer Vision, IoT Applications, Machine Learning (ML)
Keywords: student engagement, eeg-based attentiveness, computer vision, real-time attentiveness monitoring, emotion recognition

Introduction

With increasing insurmountable technology assimilation into education, opportunities, as well as the challenges that entail, are increasing. One such challenge is understanding and improving student engagement in modern learning. Student attention, interest, or concentration is a major factor in learning. Hence, considerable attention must be given to monitoring and improving it. Traditionally, student engagement is reported using qualitative methods: self-reports and teacher observations. However, both qualitative approaches, when habitually intrusive, can become disruptive to their classroom environment. Technology advances every day and has yielded real-time monitoring systems that capture a continuously objective measure of student engagement while violating their privacy the least via electroencephalogram (EEG) sensors, computer vision techniques, and other sensor-based approaches.

This paper explains in detail the student classroom attention system using EEG and image processing for objective monitoring and analyzing students engagement. The body of this paper discusses wearable EEG devices that measure brain activity, contributing to understanding students' cognitive states. Along with this, there is a face detection model using convolutional neural networks (CNN) in the image processing portion for facial expressions analysis. It analyzes both EEG data and facial expression, and thus total attention score is derived for individual and collective students' focus in real time. This score can then be interactively and conveniently displayed on a dashboard that can provide a teacher with actionable insights into what is going inside a classroom.

This application utilizes image processing to automatically count the students in the classroom, streamlining attendance management and freeing teachers from mundane tasks, so that they can engage students more meaningfully. In return, it offers real-time feedback on engagement levels to support the use of differentiated teaching strategies. Beyond its practical application, the system is also a data-driven tool for school research, as it helps analyze the impact of various teaching methods on student engagement and forms the basis for adaptive teaching techniques. The design is non-intrusive and does not disturb the classroom environment much, which is why it is suitable for large-scale use. The integration of EEG and computer vision techniques also exhibits that technology, when blended with education, can really create a better opportunity to enhance a traditional learning setting. This approach offers an enriched experience and supports interactive, dynamic adaptation in education.

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Literature survey

There have been several studies on how artificial intelligence and electronic sensors can enhance the student attention in classrooms. This review considers key findings from these studies to describe how these technologies work, what methods are being used, and the challenges they face in schools. In this survey, the link between artificial intelligence, sensors, and student engagement is established, showing how these tools can help keep students focused, support personalized learning, and make classrooms more interactive. Sulaiman et al. [1] used EEG technology to monitor student attention by analyzing alpha and beta bands with fast Fourier transform and classifying features with k-nearest neighbors and support vector machine, achieving 80.5% accuracy, despite noise sensitivity and a small sample size. Similarly, Gupta and Kumar [2] introduce a single-electrode EEG system for real-time feedback in online learning, helping teachers adapt to students' attention levels, though its performance is limited by the simple setup.

Sharma et al. [3] focus on an EEG-based system that provides real-time feedback to address attention loss in online learning, with noted challenges in signal interpretation and device optimization. Ko et al. [4] identify EEG spectral power changes as markers of attention in classrooms but is limited by its small participant sample.

Using EEG sensors, one research team attained an attunement detection accuracy of 76.82% during English lessons; it showed that attention seems to improve with time while inability to detect inattentiveness scored 50% at best without preprocessing [5]. A review by ESICM [6] recommends EEG in ICU for seizure detection, ischemia monitoring, and coma prognostication, with continuous EEG preferred in critical cases like status epilepticus and unexplained coma.

A study by Lukas et al. [7] proposes a computer vision system to monitor attendance and an estimation of student attention, aligning these with academic performance; however, further work is necessary to achieve improved accuracy and flexibility.

A face recognition-based attendance system developed by Burnik et al. [8] achieved 81.8% accuracy using discrete wavelet transform, discrete cosine transform for feature extraction, and a radial basis function classifier on 16 student images. Although it allows automation, the system requires better accuracy and adaptability in diverse classrooms. A Kinect-based system monitors student engagement in a study by Trabelsi et al. [9]. It provides real-time feedback on declining attention, helping teachers respond effectively. It helps to identify and address attention drops, enabling teachers to improve responses and outcomes effectively.

A deep-learning smart classroom system developed by Zhang et al. [10] monitors attention, emotions, and presence by using YOLOv5 monitors and feeds back to the teacher in real time. Tested on seven students, it assesses concentration and tracks behavior for improving learning environments. Thao et al. [11] developed a multimodal system employing wearable cameras and accelerometers to monitor classroom attention by measuring head motion, pen motion, and visual focus. By employing both rule-based and data-driven approaches, it achieved a highly accurate evaluation of engagement, providing insights into enhancing teaching and learning efficiency.

Sato and Tominaga [12] describe an automated system using computer vision and neural networks to monitor student attention during online lectures. It has been tested on 3,000+ videos, and it uses RNNs and facial landmarks for real-time engagement assessment, aiding educators in enhancing online learning. Krishnnan et al. [13] proposed an EduViT-based system for student attention measurement using facial expressions, with an accuracy of 66.51% but with low accuracy and incomplete engagement tracking.

Materials And Methods

In order to obtain a comprehensive assessment of student attention, we combine results from the two models: the one based on EEG signals to estimate attentiveness, and the other that employs emotion-based visual analysis. There are two methods that assess attention separately before, which are combined through a threshold's method to get the final attention score. The steps involved are as follows:

EEG attention score calculation

The methodology shown in Figure *1* for the student classroom attention system using EEG signal analysis integrates hardware and backend software components to capture, process, and analyze real-time EEG signals, assessing student attention levels during classroom activities. The system uses the MindLink EEG sensor by FT&S, which measures brainwave activity, including alpha, beta, delta, gamma, and theta waves, along with attention and meditation scores. The sensor communicates with the host system via Bluetooth for real-time data transfer, ensuring seamless integration with the processing framework.

The backend framework, implemented in Python, was designed to interface with the EEG sensor, process incoming data, and perform live calculations of attention metrics. The system records session data in CSV format, capturing essential parameters such as timestamps, raw EEG signals, brainwave amplitudes, attention and meditation scores, and computed attention levels. These attention levels are categorized into three states: low (attention $\leqslant$ 30), medium (31 $\leqslant$ attention $\leqslant$ 70), and high (attention > 70). The program incorporates mechanisms for data validation and ensures that only accurate, timestamped readings are stored for system records session data in CSV format, capturing analysis.

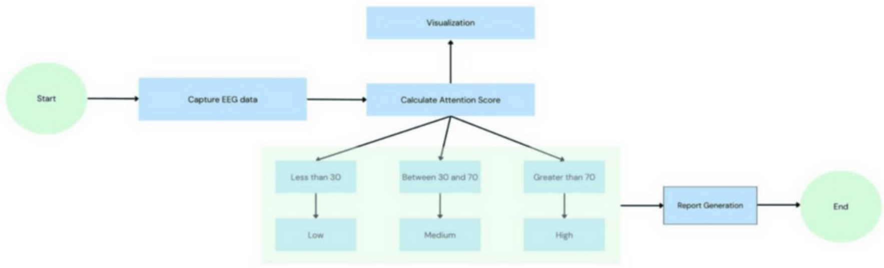

FIGURE 1: EEG Analysis Workflow

EEG, Electroencephalogram

Before the start of a session, the user is prompted to input metadata, including the student’s name, roll number, and session details. The recording process then begins, during which the system streams EEG data from the sensor. For each data point, it calculates the corresponding attention level based on thresholds and logs the results in a structured format. Real-time metrics are updated and stored in session-specific files for further analysis. The backend also computes cumulative attention states over the session's duration, including total times spent in low, medium, and high attention levels.

The analysis results are aggregated into a cumulative class summary file, which provides an overview of attention metrics across multiple sessions. This backend summary generation ensures that educators can access detailed reports for evaluating and comparing student engagement over time.

This integrated approach ensures accurate, real-time monitoring of student attention levels and provides actionable insights into classroom engagement. By focusing on backend data processing and analysis, the system emphasizes reliability and scalability, making it a powerful tool for enhancing the learning experience.

Image processing attention score calculation

Dataset

In this paper, we used the Facial Expression Recognition (FER-2013) dataset [14] - a common and extensive FER dataset of 35,887 grayscale images, each of size 48 × 48 pixels, mostly available publicly for emotion recognition. The emotions depicted in the images are divided into seven types: anger, disgust, fear, happiness, sadness, surprise, and neutral emotions.

Emotions	No. of images
Neutral	6,198
Happy	8,988
Sad	6,077
Angry	4,759
Surprise	4,002
Fear	5,121
Disgust	547
Total	32,692

TABLE 1: Overview of FER-2013 Dataset

FER, Facial Expression Recognition

The distribution of images across these classes, as shown in Figure 2, is detailed in Table 1.

FIGURE 2: Sample of Image Processing Dataset

CNN model for emotion recognition: The CNN model for emotion recognition uses four convolutional modules with batch normalization, rectified linear unit activation, pooling layers, separable convolutions, and residual connections for efficiency and stability. A global average pooling layer consolidates feature maps, and a softmax output layer classifies emotions into five categories based on the FER-2013 database.

Ensemble learning for emotion recognition: The ensemble approach trains two CNN models with original and horizontally flipped images to counter facial symmetry. Both models' predictions are concatenated and passed through a dense layer to integrate features; finally, a softmax output classifies the model with high accuracy.

System Architecture

The system shown in Figure 3 combines CNN-based emotion recognition and face recognition for real-time student surveillance. The CNN model, trained on the FER-2013 database, evaluates students' emotions to assess attention levels based on facial expressions. Face recognition, implemented using the face_recognition library, identifies and matches students' faces from a dataset. With real-time video input, the system tracks faces, analyzes emotions, and evaluates concentration or distraction levels effectively.

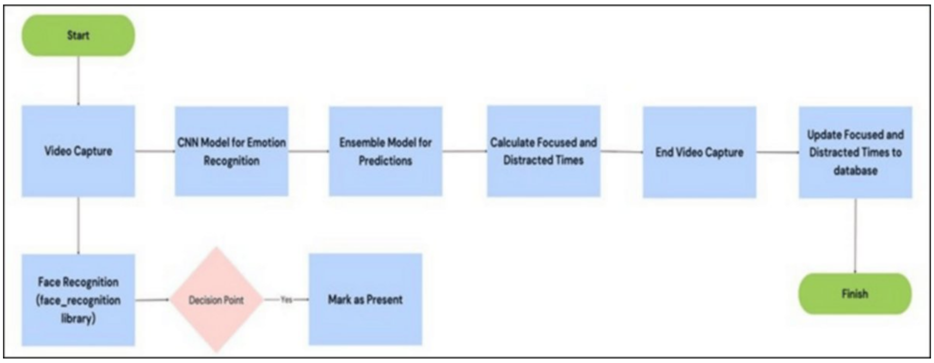

FIGURE 3: Image Processing Workflow

Data Collection and Preprocessing Data Loading and Transformation

The system takes FER-2013 images and processes them into 48 × 48 normalized grayscale arrays with one-hot encoded labels. It enhances training diversity and reduces overfitting with real-time data augmentation, which includes rotation, shifts, and flipping.

Face Recognition Process

Face recognition uses the face_recognition library. Encoding Known Faces: Preprocesses and stores encodings of known students for reference. Real-Time Identification: Detects, crops, and encodes aces in video frames, comparing them to known encodings to identify students and mark them present. The application monitors the attendance and attentiveness of students using face recognition and emotion detection, with the focus and distraction times stored in a CSV file. It marks the detected students as "Present" while increasing the focus time with "Neutral" and others with emotions increase distraction time. When the session ends, it logs focus, distraction, and session times, marking undetected students as "Absent."

Integration of EEG score and image processing score

Based on the integration of EEG scores with CNN-based emotion recognition, determination of whether a student is "Focused" or "Not Focused" combines analysis of neural activity and facial expressions. The decision logic in the following rules:

Case 1: both EEG ⩾ 40 and CNN neutral expression, then "Focused."

Case 2: EEG ⩾ 40, indicating focus. CNN picks up a non-neutral expression, so it says "Not Focused."

Case 3: EEG <40 indicates not focused, even when CNN has picked up a neutral expression, hence "Not Focused."

Case 4: Since EEG (<40) and CNN (non-neutral) output shows he was not focusing, "Not Focused."

The classification process includes comparing EEG attention scores (⩾40 as "Focused") and CNN model outputs, into the outcome based on defined rules for a reliable and holistic assessment of student attention.

Results

The system assesses the attentiveness of students through EEG-based brainwave analysis and image processing for real-time emotion detection and face recognition, providing a holistic view of attention levels. Distinct patterns were observed, with high beta and gamma waves indicating intense focus and alpha waves reflecting relaxation. The system accurately tracked transitions between low, medium, and high attention levels, as confirmed by attention score trends plotted with brainwave data.

EEG analysis

Figure *4* shows high attention, which reflects in graph as it is tilted towards high beta frequency.

FIGURE 4: High Attention State

Image processing

Figure 5 shows the training on original data (xtrain and ytrain) with augmentation through ImageDataGenerator. This model adapts to features from standard data.

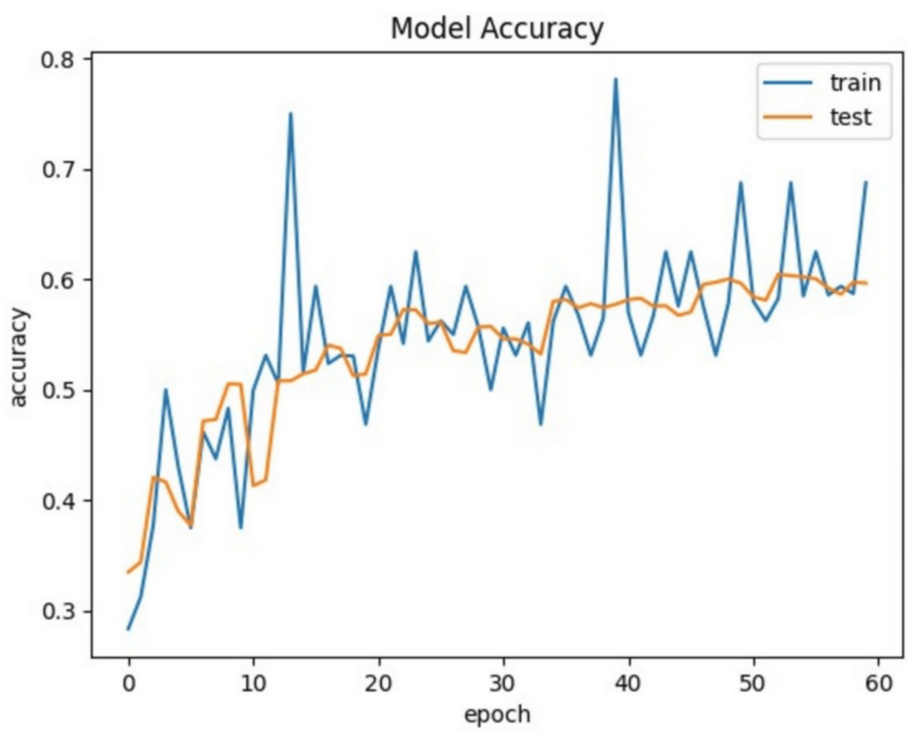

FIGURE 5: Training Accuracy of Image Processing

Confusion matrix with these labels are shown in Figure 6. Emotion labels (0-6): 0: Angry, 1: Disgust, 2: Fear, 3: Happy, 4: Sad, 5: Surprise, and 6: Neutral.

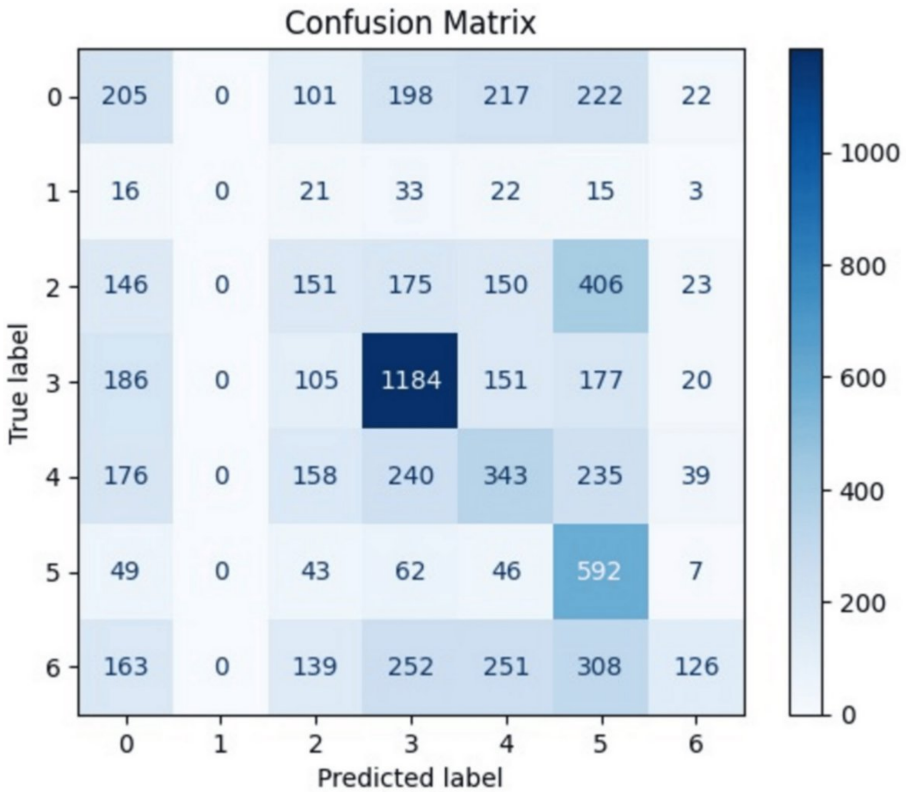

FIGURE 6: Confusion Matrix

Figure 7 shows the real-time outcome of image processing.

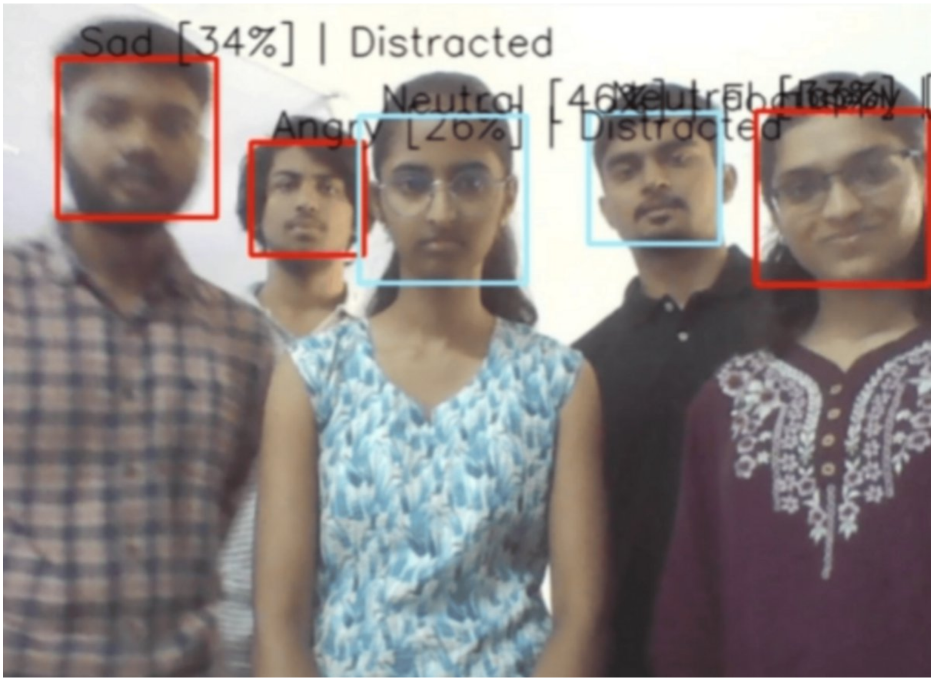

FIGURE 7: Real-Time Outcome of Image Processing

Discussion

The future horizon of this project would be to incorporate alternative wearable devices like wristbands or other less invasive in nature to enhance comfort levels among the users, and the reliability of data gathered for the sake of tracking engagement can make the students more willing to accept it. Additionally, with the introduction of high-definition cameras within classrooms, facial recognition can significantly be enhanced because they record more aspects of the face for enhanced monitoring of attendance and measurement of students' engagement adequately. Further towards the future, integration with learning management system (LMS) for real-time data exchange, i.e., educators also monitoring emotional engagement and participation, correlating the emotional and focus states of students to academic performance and welfare; adaptation, based on individualized needs, to an ideal learning environment tailored to the student.

Conclusions

The proposed system provides a new approach to attendance and engagement monitoring through facial recognition and emotion detection, with dynamic measurement of focus and distraction levels during learning activities. Future developments include integrating less-invasive wearable devices, such as wristbands, to enhance user comfort and data accuracy, as well as employing high-definition cameras for improved facial recognition and more precise tracking of attendance and engagement. The integration into LMS will allow for data exchange in real-time, thereby enabling educators to monitor emotional engagement, correlate states of focus with academic performance, and create customized learning environments. This innovative solution aims to deliver accurate attendance records and actionable insights, thereby filling the gap within current educational challenges and setting the way to a more responsive and supportive learning environment.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Intellectual property info:** The authors intend to file a patent for the system described in this article. . **Other relationships:** The images used in the article are of the authors themselves. Therefore, no separate consent is required for displaying the faces of the participants.

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