

EduPulse: An AI-Driven Emotion And Engagement Analytics System For Smart Classroom Learning

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Abstract

The increasing popularity of digital educational platforms requires intelligent systems which can track student participation and emotional states during learning sessions. The research presents EduPulse an AI-powered educational system which tracks student emotional states and their learning engagement in real time to improve teaching effectiveness and student achievement. The system implements computer vision technology with deep learning algorithms to analyze facial expressions and body movements and eye contact through camera surveillance. The system detects six different emotional states which include confusion and boredom and interest and attentiveness based on the observed behavior patterns during the classroom lectures. The system processes collected information through machine learning methods which the interactive analytics dashboard utilizes to present teachers with data about general student participation and their focus levels and academic challenges. The system produces automatic recommendations which assist teachers in adjusting their teaching methods through two main approaches. The platform includes privacy protection features which safeguard educational data and ensure responsible artificial intelligence practices in schools. The proposed conceptual framework demonstrates how artificial intelligence and emotion recognition technologies can transform traditional classrooms into intelligent learning environments. EduPulse provides educational institutions with real-time student engagement metrics which lead to better teaching results and increased student involvement and customized learning pathways through its interactive learning environment.

***Keywords:** Emotion Recognition, Smart Classroom Systems, Student Engagement Monitoring, Artificial Intelligence in Education, Computer Vision, Deep Learning, Real-Time Learning Analytics, Educational Data Privacy.*

1. Introduction

1.1. Background And Motivation

The educational sector has undergone a major shift in recent times due to the introduction of modern technology in the educational system. The major challenge that has been faced by the educational sector in traditional classrooms as well as in online classrooms is the real-time monitoring of the performance and engagement levels of the students. The recent advancements in the field of artificial intelligence, computer vision technology, and emotion recognition technology have made it possible to develop an efficient system to overcome the aforementioned challenge. The traditional

learning analytics system can be used for the monitoring of the attendance and performance of the students, whereas video conferencing can be used in online classrooms; however, this technology does not provide detailed information regarding the engagement levels of the students. EduPulse is an efficient smart classroom system that uses computer vision and artificial intelligence technology, i.e., deep learning technology for the recognition of the emotional states of the students, i.e., the levels of concentration and confusion, etc.

1.2. Objectives

The study has following objectives:

- The primary objectives and objectives of this

current study are as follows:

- To develop a smart classroom system with different AI technologies to monitor and detect the emotional states of the students in real time.
- To incorporate different computer vision technologies to detect emotions based on the facial, body, and eye movements of the students.
- To incorporate different data analytics methodologies to generate insights.
- To develop an interactive and user-friendly dashboard to interact with the system.
- To develop a robust, scalable, and secure framework to deploy the system in different classrooms.

2. Literature Review

2.1. Emotion Recognition And Student Engagement Systems

Over time, a number of technologies have come up to support the digital learning process, but getting insights into students' engagement in real-time is a major challenge. In most learning management systems, educators are provided with data related to students' attendance and grades, but they are not provided with any idea of students' emotional responses to the content being delivered to them. Even though technology has shown promise in helping create a strong online learning environment, it has not succeeded in giving educators a clear idea of students' engagement during lessons. The existing AI applications, based on face recognition, have been designed to measure students' responses to lessons, but most of them are designed for general use only.

2.2. Computer Vision In Emotion Detection

The domain of emotion recognition has been enhanced with deep learning models, unlike traditional models that depended on feature extraction, which was usually influenced by various factors such as lighting, noise, and facial expressions. This has been achieved by using convolution neural networks to efficiently identify facial expressions, eye movements, and head positions.

The models are able to recognize various behavioral

signals such as attention, confusion, and interest in a dynamic learning environment where various movements are taking place. Moreover, AI models utilize such advanced emotional states during learning, which is an essential cognitive and learning process.

2.3. Speech Recognition And Tts For Accessibility

One aspect of this is the role that machine learning plays in the processing of significant student data sets, enabling educators to identify patterns and forecasts to guide educational decisions. One of the trends in data visualization in educational settings is the use of interactive dashboards. Although there is existing functionality in the architectures that has the fundamental ability to execute post-hoc classification studies, there is no existing functionality that has the ability to execute real-time feedback for the instructor. The objective of this research is to address this issue through the integration of real-world emotion recognition and intelligent analytics.

3. System Architecture and Workflow

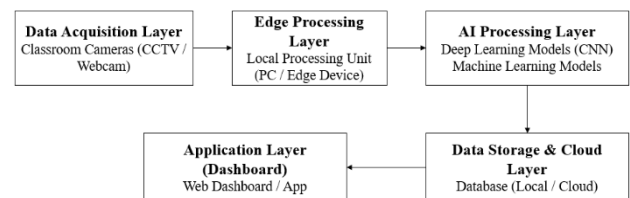


Figure 1 System Architecture

In Figure 1 Hardware Components: On the other hand, EduPulse is a smart system that keeps a keen eye on the students through the use of cameras and edge computing devices. The cameras are installed where they are able to capture the facial expressions, posture of students, and eye movements of the students in the classroom. The cameras are able to adjust to the changing lighting conditions. However, what makes EduPulse unique and remarkable is that it is able to respond to any situation that might arise. This is due to the fact that the system does not completely rely on the cloud for its operation. Instead, it mainly depends on edge computing devices. This makes it possible for the system to respond to any situation that might arise without any

delay. In addition to the use of cameras, EduPulse is also able to use microphones to capture all the sounds. Furthermore, the system is also able to use Wi-Fi or Bluetooth for efficient communication shown in Figure 2.

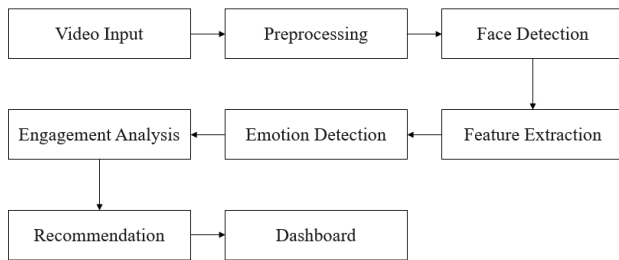


Figure 2 Software Architecture

Software Architecture : The software provided by EduPulse has a pipeline with different stages to ensure efficient monitoring and analysis of the engagement of students in a classroom. **Video Collection:** The first stage of the pipeline of the EduPulse software is the collection of videos by placing cameras in different locations in the classroom. **Preprocessing:** In this stage of the pipeline of the EduPulse software, the collected videos are preprocessed to ensure the quality of the collected videos. This stage of the pipeline includes the reduction of noise, improvement of images, and normalization. **Analysis Using Computer Vision and Deep Learning:** In this stage of the pipeline of the EduPulse software, computer vision and deep learning techniques like Convolutional Neural Networks (CNN) are used to analyze the collected videos. This stage of the pipeline includes the identification of images, expressions, eye movements, and head movements of the students present in the classroom. **Emotion Classification:** This stage of the pipeline of the EduPulse software includes the classification of emotions like attention, confusion, boredom, etc. based on the images, expressions, etc. of the students present in the classroom. This software works efficiently in a crowded classroom scenario. **Engagement Evaluation and Dashboard Presentation:** The aggregated data is presented to the educator with the help of different machine learning algorithms, so that a clear idea about the level of engagement of the

students is achieved and presented in a simple yet effective manner. **Privacy and Integration:** Throughout the process, strict privacy conditions are followed so that there is no violation of the students' data and the system is designed in an efficient manner so that it can be integrated into the existing environment, thus making the system practical and achieving a better result for the students. With the help of the above-discussed process, EduPulse is able to provide the educator with valuable insights so that a more responsive and engaging environment for the students is achieved.

4. Experimental Framework & Performance Indicators

For testing the actual effectiveness of EduPulse in real-time scenarios, extensive testing has been conducted in both controlled environments and real-world environments. In order to test the actual effectiveness of the emotion recognition module, well-established and accurate data sets like FER-2013 and CK+ are made use of, as these data sets contain diverse images of facial expressions. Apart from testing the actual effectiveness of the system, actual video recordings are made in classrooms to test the actual effectiveness of the system in real-world classroom environments. The actual effectiveness of the system is verified based on actual student behaviors. Apart from testing the actual effectiveness of the emotion recognition module, the actual effectiveness of the speech recognition module is also verified as part of actual effectiveness testing. The actual effectiveness testing is conducted based on accuracy, precision, recall, and F1 score. The actual effectiveness testing shows that the system is highly accurate, as it is able to achieve more than 90% accuracy in classifying the emotions of the students. Moreover, the actual effectiveness testing shows that the response time of the system is extremely fast, as it operates within two seconds.

5. Future Enhancements And Scope

Although this system is an enhancement in its own right, there are certain areas that can be targeted to bring growth in the future.

5.1.Enhanced Deep Learning Models For Emotion Detection

The future development in the system can be made

to incorporate self-learning AI models that have the capability to learn and improve their performance by learning. The system can also be made to incorporate various models of recognition, not limited to facial expressions, but voice and gestures as well. This can be helpful in improving the efficiency of the system.

5.2. Real-Time Cloud Integration And Scalability

Although the real-time processing has the advantage of being efficient in terms of response time, the integration of cloud services using federated learning can be helpful in improving the scalability of the system.

5.3. Enhanced Analytics And Personalization

The future development in the system can be made to incorporate the analytics of the system to provide information regarding the level of subject difficulties. This can be helpful in providing support in the form of AI.

5.4. Role Of Multimodal Interaction And Smart Interface

Voice commands and gestures may also be included in the system. In addition, augmented reality may also be a game-changer in efficient representation of classroom scenarios. This may be a major factor in teaching/learning.

5.5. Role Of Multi-Language And Cross-Cultural Adaptation

The system may be made more user-friendly by incorporating multiple regional languages. Emotion recognition models may be trained to recognize cross-cultural emotions. This may be a major factor in enhancing emotion recognition.

5.6. Role Of Security And Ethical Considerations

Diversity in emotion recognition models may be of extreme importance. This may help in ensuring that there is no bias in emotion recognition. In addition, anonymization may be a major requirement in ensuring ethical usage of student data.

5.7. Role In Real-World Deployment And Adoption

The primary target for testing the efficiency of the system would be educational institutions. Cooperation with the educational system would allow for easier adoption of the system and make it even more applicable to real-world use.

With these aspects in mind, EduPulse has the potential to become a wiser, flexible, and moral system, hence enhancing its ability to impact modern education.

Conclusion

The need for the development of an adaptive and intelligent learning environment has led to the quest for innovative solutions that can help in the development of an enhanced teaching-learning process in an efficient manner. EduPulse is a smart classroom solution that utilizes AI for the development of an emotion detection system for the students. One of the most important features that have been associated with the EduPulse smart classroom solution is that it provides emotion recognition and engagement analytics for the teachers in an efficient manner. It is important to mention that the EduPulse smart classroom solution has been able to provide an opportunity for the teachers to make decisions in an efficient manner while maintaining a high level of privacy. The experimental outcomes that have been achieved for the EduPulse smart classroom solution have been able to provide high accuracy and efficiency with respect to the usage of the solution in a classroom environment. Thus, to conclude the research, it is important to mention that there is a high potential to revolutionize the traditional learning environment to a smart learning environment with the help of AI. Future Work Looking into the future, this work has shown the potential to improve this solution using new AI techniques. Therefore, EduPulse has the potential to play an important role in the future of smart education.

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