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RESEARCH ARTICLE

# Real-Time Student Engagement Monitoring System

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**ABSTRACT**
In today's rapidly evolving educational landscape, digital learning platforms play a vital role in modern education. However, monitoring student engagement during online or hybrid sessions remains a significant challenge. Traditional observation methods are often subjective, time-consuming, and impractical for large classrooms.This project presents a Real-Time Student Engagement Monitoring System that uses Computer Vision and Artificial Intelligence (AI) to automatically detect and analyze student attentiveness. The system captures live video through a standard webcam and utilizes MediaPipe's FaceMesh model to extract facial landmarks. Key parameters such as Eye Aspect Ratio (EAR) and head yaw angle are computed to classify engagement levels into three categories: Attentive, Confused, and Distracted.An interactive Streamlit dashboard displays real-time analytics, including engagement percentage, attention trends, and time-based insights. The system also records engagement data for post-session analysis, enabling educators to identify inattentive periods and improve teaching strategies.This lightweight and cost-effective solution demonstrates the practical application of AI in education. It enhances teaching effectiveness and supports personalized learning by bridging the gap between traditional observation and digital learning environments.
**Keywords:** *Student Engagement, Computer Vision, Artificial Intelligence, Eye Aspect Ratio (EAR), Head Pose Estimation, MediaPipe FaceMesh, Real-Time Monitoring, Streamlit Dashboard, Learning Analytics, Online Education.*

## INTRODUCTION

### The Pre-Historic Life of Chandel/Tengnoupal Naga People:

In recent years, the field of education has experienced a major shift toward digital learning environments. Online classes, e-learning platforms, and hybrid modes of teaching have become essential components of modern education systems, especially after the global pandemic accelerated the adoption of virtual classrooms. While technology has made learning more accessible and flexible, it has also introduced new challenges for teachers—particularly in maintaining and assessing student engagement during virtual sessions. Engagement and attentiveness are key factors that directly influence learning effectiveness, comprehension, and overall academic performance. Without proper monitoring, students may become distracted, disengaged, or passive participants in online classes.

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Traditionally, in physical classrooms, teachers can observe students' body language, eye contact, and reactions to gauge attentiveness. However, such direct visual cues are not easily available in digital learning platforms, making it difficult for educators to determine whether students are focused, confused, or distracted. This challenge has motivated the development of AI-powered engagement monitoring systems that can automatically evaluate and provide feedback on student attentiveness using computer-based analysis.

The Real-Time Student Engagement Monitoring System presented in this project is designed to address this issue by leveraging Computer Vision and Artificial Intelligence techniques. The system uses a webcam to capture live video of a student during a learning session. Through MediaPipe's FaceMesh model, facial landmarks such as the eyes, nose, and head orientation are detected and analyzed in real time. Using these data points, important metrics like the Eye Aspect Ratio (EAR) and head yaw angle are calculated. The EAR helps determine whether a student's eyes are open, closed, or blinking excessively—indicating focus or fatigue—while the yaw angle helps detect whether the student is looking away from the screen, which often signifies distraction.

Based on these facial and positional features, the system classifies engagement levels into three categories: Attentive, Confused, and Distracted. These results are continuously updated and displayed using an interactive Streamlit-based dashboard, which provides visual insights into student engagement trends through graphs and metrics. Additionally, all engagement data are stored in a CSV log file for post-session review and analysis, helping educators identify patterns such as when students tend to lose focus or become disengaged. The system is designed to be lightweight, affordable, and efficient, requiring only a standard webcam and a computer with basic processing power. It operates in real time, ensuring that both teachers and students can benefit immediately from the engagement feedback.

This project demonstrates the potential of AI and Computer Vision to improve digital learning experiences by making online education more interactive, personalized, and effective. By providing an automated and objective method to measure student attentiveness, the system supports educators in adapting their teaching strategies, enhancing participation, and improving overall learning outcomes. Thus, the Real-Time Student Engagement Monitoring System serves as a valuable step toward intelligent education systems that combine technology with human-centered learning.

## 2. Literaturesurvey

### i. Soukupová & Čech (2016) — Eye Aspect Ratio (EAR) / Blink Detection

Soukupová and Čech proposed the Eye Aspect Ratio (EAR) method to detect eye blinks using facial landmarks. EAR is a simple geometric ratio computed from eye landmark coordinates; when it falls below a threshold, a blink or closed-eye state is detected. The method is lightweight, robust for video streams, and widely used as a baseline for drowsiness and attention monitoring because it does not require training large models. Many subsequent systems have adopted EAR for real-time blink and fatigue estimation.

### ii. Xie et al. (2023) — Student Engagement Detection from Webcams

This work presents a webcam-based engagement detection system that combines multi-dimensional facial features with classifiers to predict engagement states in online classrooms. It demonstrates the feasibility of per-student webcam analysis and highlights the importance of data labeling, privacy-aware data collection, and multimodal features (facial and behavioral cues) to improve classification accuracy.

### iii. Hasnine et al. (2021) — Emotion Extraction and Visualization for Online Lectures

Hasnine and colleagues focused on extracting emotional cues from students during online lectures and visualizing engagement levels. They integrate facial expression recognition with analytics dashboards to help instructors identify low-engagement periods. This work supports the use of visualization dashboards in monitoring systems.

### iv. Head-Pose and Attention Studies — Attention Span Prediction

Several studies demonstrate that head-pose estimation (yaw, pitch, and roll) serves as a reliable indicator of gaze direction and attention in webcam-based systems. These approaches use pose features to predict attention levels and show that head orientation alone can effectively indicate distraction or engagement.

### v. Real-Time Eye Blink Detection Using General Cameras (2023)

Recent studies have extended EAR-based blink detection to work reliably on low-quality webcam feeds under varying lighting and frame rate conditions. These works validate that EAR-based methods remain effective on standard hardware, supporting the feasibility of non-intrusive engagement monitoring systems.

### vi. Surveys on Head-Pose Estimation and Deep Learning (2023–2024)

Recent surveys compare classical geometric head-pose estimation methods (such as PnP and landmark-based approaches) with deep learning-based models. While geometric methods are lightweight and interpretable, deep models offer higher accuracy at the cost of computational complexity. This supports the use of hybrid approaches for balancing performance and efficiency.

## 3. Problem Statement

With the rapid growth of online and hybrid learning, monitoring student engagement in virtual classrooms has become a major challenge for educators. Unlike traditional classrooms, teachers cannot easily observe facial expressions, eye contact, or body language to assess attentiveness. As a result, determining whether students are focused, confused, or distracted is difficult in digital environments.Current engagement monitoring methods are often manual, subjective, and not scalable for large classes, leading to inaccurate evaluation of student participation and reduced learning effectiveness. Additionally, many existing solutions rely on expensive hardware or intrusive data collection techniques, limiting their practical adoption in educational institutions.Therefore, there is a need for a cost-effective, non-intrusive, and automated system that can analyze student engagement in real time. The proposed solution aims to leverage computer vision and artificial intelligence to classify attentiveness and provide meaningful insights to educators, ultimately improving teaching and learning outcomes.

**4. Proposed Model**

The main purpose of the Real-Time Student Engagement Monitoring System is to design and implement an intelligent solution capable of automatically analyzing, monitoring, and classifying a student's level of engagement during online or classroom learning sessions. In traditional classrooms, teachers can observe students' behavior, facial expressions, and body language to assess attentiveness. However, in digital learning environments, such direct observation is limited, making it difficult to determine whether students are actively engaged.To address this challenge, the proposed system adopts a technology-driven approach using Computer Vision and Artificial Intelligence (AI). It captures live video input through a standard webcam and processes facial data using MediaPipe FaceMesh, which extracts facial landmarks in real time. Based on these landmarks, the system computes key metrics such as the Eye Aspect Ratio (EAR) to monitor blinking patterns and the head yaw angle to estimate gaze direction. These features are then used to classify engagement levels into three categories: Attentive, Confused, and Distracted.Beyond classification, the system provides real-time insights through an interactive Streamlit-based dashboard, displaying engagement statistics, trends, and session summaries. This enables educators to identify disengaged students and adapt their teaching strategies accordingly.Additionally, engagement data are stored for post-session analysis, supporting long-term evaluation of learning patterns and helping institutions enhance teaching effectiveness. Overall, the proposed model offers a lightweight, cost-effective, and non-intrusive solution that makes digital learning more interactive, data-driven, and personalized.

**5. System Model**

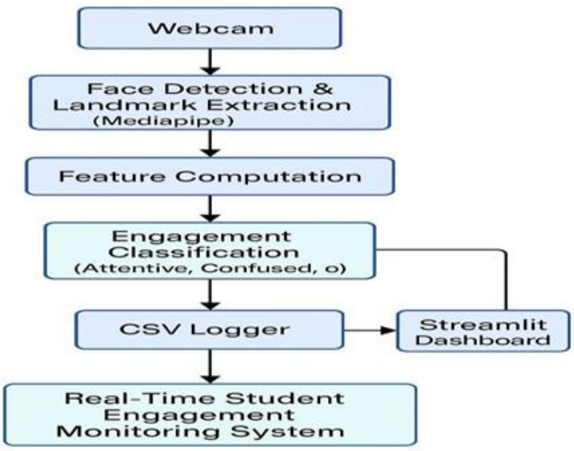


**Fig 5.1.System Model**

Figure **(5.1)** illustrates the workflow of the Real-Time Student Engagement Monitoring System. The system captures live video using a webcam and processes it with MediaPipe FaceMesh to extract facial landmarks. Key features such as Eye Aspect Ratio (EAR) and head yaw angle are computed to analyze student attentiveness. Based on these features, the system classifies engagement into three categories: Attentive, Confused, and Distracted.The results are stored in a CSV file for record-keeping and future analysis. A Streamlit dashboard visualizes real-time engagement data through graphs and statistics, enabling educators to easily understand student behavior and attention trends. The system operates efficiently on standard devices without requiring specialized hardware.Overall, the model provides real-time monitoring and meaningful insights to enhance teaching effectiveness and improve learning outcomes.

**6. Modules**

**a. Load Data**

The first step involves loading and preparing engagement data recorded during real-time sessions. The system generates its own dataset from webcam analysis and stores it in a CSV file (e.g., session_data.csv). Each record contains information such as timestamp, Eye Aspect Ratio (EAR), head yaw angle, and engagement state (Attentive, Confused, or Distracted). This dataset is loaded using the Pandas library for further analysis and visualization.

### b. Data Cleaning
After loading the data, it is cleaned to ensure accuracy and consistency. Missing values in EAR and head yaw angle are handled using mean or median imputation. Duplicate records and inconsistent labels are removed, and outliers caused by poor lighting or sudden movements are filtered out. This step ensures that the dataset is reliable and ready for analysis.

### c. Feature Engineering
In this stage, new features are derived to improve engagement detection accuracy. These include Average_EAR (mean eye openness), Yaw_Deviation (variation in head movement), Focus_Score (a combined metric of EAR and yaw), and Engagement_Duration (time spent in each engagement state). These features help in better interpretation of student behavior.

### d. Merge Datasets
Multiple session-based CSV files are merged into a single structured dataset. Data from different sessions is aligned using timestamps and identifiers, ensuring consistency and eliminating duplicates. This combined dataset enables comprehensive analysis of engagement trends over time.

### e. Aggregation and Analysis
The data is aggregated to identify behavioral patterns and engagement trends. This includes analyzing engagement over time intervals, calculating average EAR and yaw values, and determining the time spent in each engagement state. Visualization techniques such as graphs and charts are used to present insights effectively.

### f. Encoding Categorical Variables
Categorical variables, such as engagement states, are converted into numerical form for analysis. Label encoding assigns integer values to each category, while one-hot encoding creates binary columns. This ensures compatibility with analytical tools and future machine learning models.

### g. Build Engagement Detection Model
A lightweight rule-based model is implemented for real-time engagement classification. Based on EAR and head yaw values, the system classifies students as Attentive, Confused, or Distracted. This approach ensures fast processing without requiring large datasets or complex training.

### h. Evaluate Model
This system is evaluated to ensure performance and reliability. Metrics such as accuracy, latency, frame rate (FPS), and consistency under different conditions are measured. The model achieves real-time responsiveness and stable performance, making it suitable for practical classroom applications.

## 7. Screen Shots
Develop the real-time monitoring script using OpenCV and MediaPipe FaceMesh to capture webcam input, compute EAR and head yaw angle, classify engagement levels, and store results in log files.
Create a Streamlit dashboard to load CSV logs, visualize engagement data using charts, and provide real-time updates with auto-refresh functionality.

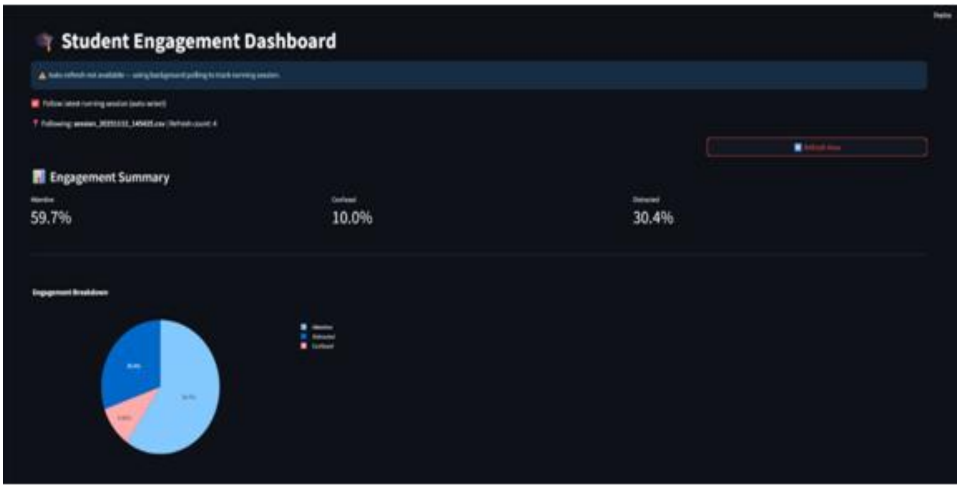


**Fig7.1: User Interface**

Run the monitoring script and dashboard together to validate real-time classification accuracy, ensure proper dashboard updates, and test system reliability under varying lighting conditions and user positions.

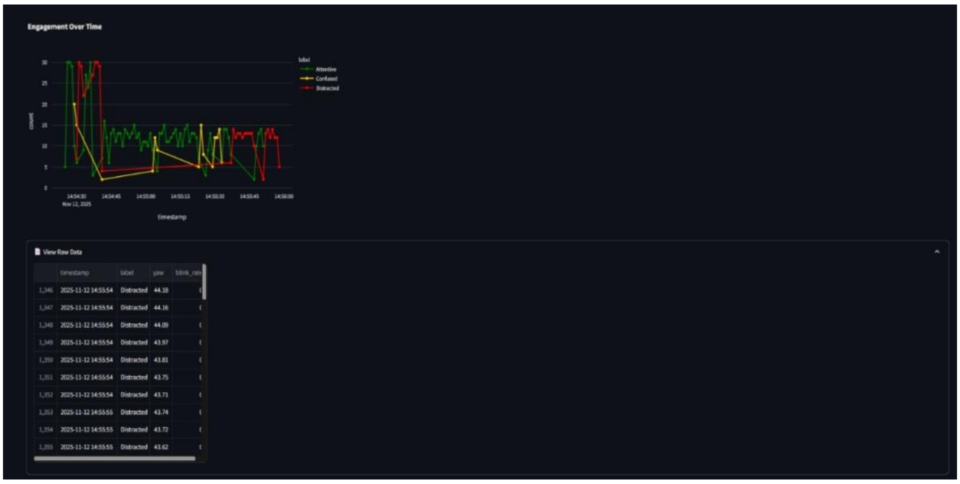


**Fig 7.2: Engagement Overtime**

Package the system into an executable setup, provide user guidelines for running the monitor and dashboard, and deploy it on standard laptops for classroom or online learning use.


**Fig 7.3: Confused**

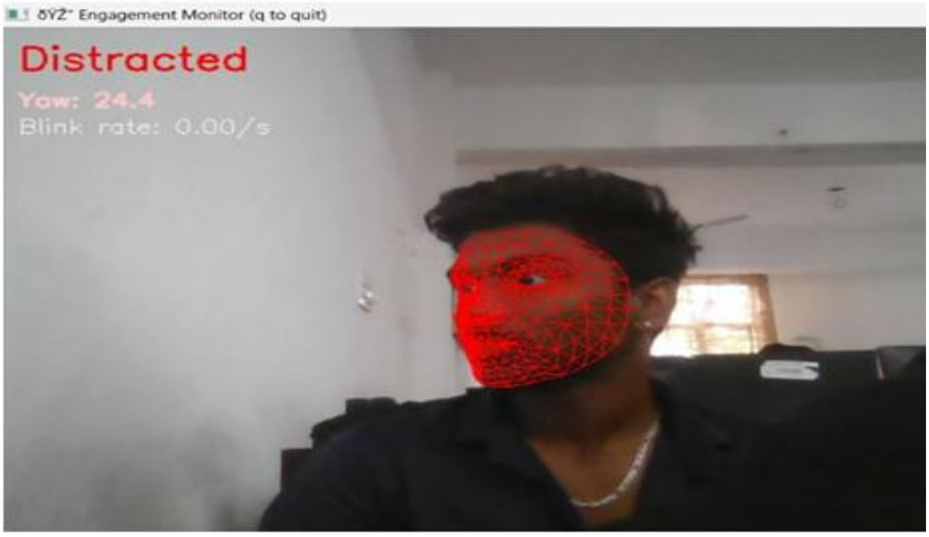


**Fig 7.4: Distracted**

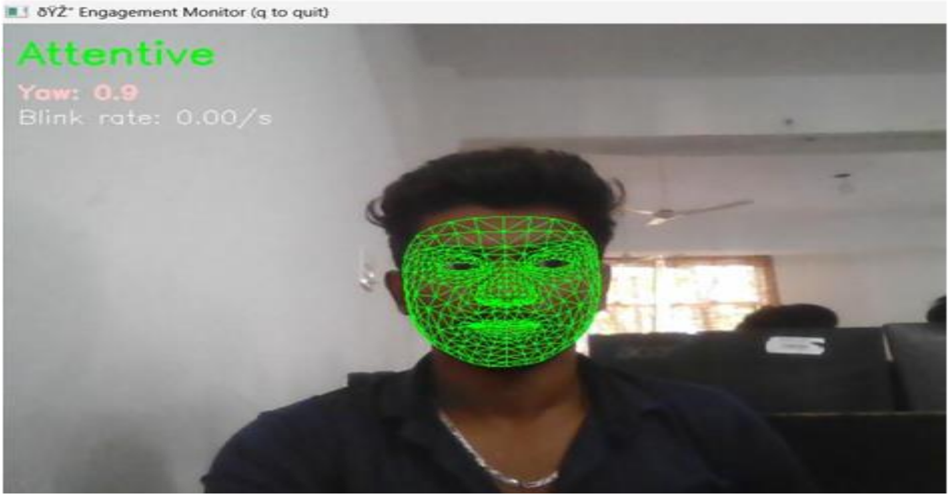


**Fig 7.5: Attentive**

## 8. Conclusion

The Real-Time Student Engagement Monitoring System successfully demonstrates how Computer Vision and Artificial Intelligence (AI) can be applied to enhance learning experiences in modern education. The project focuses on detecting and analyzing student attentiveness during online or offline classes using facial cues such as Eye Aspect Ratio (EAR) and head yaw angle derived from MediaPipe FaceMesh.Through real-time webcam input, the system accurately classifies engagement into three categories—Attentive, Confused, and Distracted—providing immediate and valuable feedback for educators. The integration of a Streamlit dashboard enables live visualization of engagement data through charts, graphs, and session summaries, making it easier to interpret student behavior and attention levels.The system has been tested for accuracy, speed, and usability, achieving reliable real-time performance on standard computing devices without requiring specialized hardware. Its lightweight, rule-based design ensures efficiency while maintaining sufficient accuracy for effective classroom analysis.This project bridges the gap between traditional face-to-face observation and online teaching environments by offering a data-driven solution for understanding student participation. The insights generated can help teachers adapt instructional methods, identify disengaged students, and improve overall learning outcomes.In conclusion, this system represents a practical step toward intelligent education technologies. With further enhancements, it has the potential to evolve into a comprehensive AI-based platform that supports both educators and learners in creating more engaging and personalized learning experiences.

## 9. Future Scope

The Real-Time Student Engagement Monitoring System provides a strong foundation for intelligent learning analytics and automated classroom monitoring. While the current system effectively detects and visualizes student engagement in real time, several enhancements can be explored in the future:

- **Multi-Student Tracking:**
  Extend the system to monitor multiple students simultaneously using face detection and tracking techniques.
- **Machine Learning Integration:**
  Incorporate advanced deep learning models such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) to improve engagement prediction accuracy.
- **Emotion and Sentiment Detection:**
  Add facial emotion recognition to detect states such as happiness, boredom, confusion, or frustration for deeper behavioral analysis.
- **Audio and Speech Analysis:**
  Integrate voice and speech recognition to correlate verbal participation with visual engagement.
- **Cloud and LMS Integration:**
  Connect the system with Learning Management Systems (LMS) or cloud platforms to store and analyze engagement data at scale.
- **Mobile and Web Deployment:**
  Develop mobile and browser-based versions to improve accessibility across devices such as smartphones and tablets.
- **Personalized Learning Insights:**
  Utilize collected data to provide customized feedback to both students and educators, enabling adaptive teaching strategies based on individual engagement patterns.

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