AI-Powered Student Monitoring for Smart Classrooms using ML

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***Abstract-* Student behavior plays a vital role in improving and maintaining student involvement and discipline for better academic outcomes. The current study proposes an integrated framework that detects activities like sleeping, eating, and using mobiles during class hours and notifies the faculty in real time. It also tracks student attendance. The integration of Artificial Intelligence has become essential in classrooms. This system integrates computer vision algorithms, which includes YOLOv8 for object detection, MediaPipe for facial and hand movement recognition and Twilio WhatsApp API, which sends notifications directly to the faculty whenever a student is detected doing any inappropriate activity like above mentioned activities. In this study, we collected classroom footage and applied techniques like frame filtering, face alignment and activity annotation. We compared deep learning models like YOLOv7, YOLOv8 and EfficientDet for the highest performance; among these, YOLOv8 has the highest detection accuracy of 94.87%, recall of 95.76% and an F1-score of 94.01%. Face recognition models like FaceNet and Dlib are used for attendance tracking, with FaceNet achieving an accuracy of 96.45%. Compared to old manual monitoring techniques, our system delivers better accuracy and enables faculty response faster. This system covers the gap in traditional classroom monitoring and provides an innovative and automatic solution to improve student discipline and engagement. Supporting swift action while lightening the load of faculty, this solution combines deep learning and real-time notifications. This research makes a noteworthy contribution to the development of intelligent educational environments and encourages the use of ethical AI to develop more accurate smart analysis approach models on data up to October 2023.**

***Keywords:* Computer vision, Deep learning, Real-time notifications, FaceNet, MediaPipe.**

I. INTRODUCTION

In a constantly changing educational landscape, AI technologies have been key in transforming traditional learning environments into smart, data-driven systems. HAR is an important application of AI in education which allows for real-time monitoring of students to improve engagement, boost performance, and detect anomalies like inattention or use of mobile phones in class.

There have been recent studies showcasing the increasing applications of HAR and machine learning as tools for classroom activity monitoring, disengagement detection, and participation assessment. A model for identifying student engagement through posture and facial cues was proposed by Alrawis and Zakariah in [1]. In their extended work, they used deep learning to classify active versus passive behaviors regarding e-learning [2]. Brahim [3] predicted academic performance based on online activity data and found a correlation between behavior and outcome. While earlier HAR systems relied on a single data type, such as using microphones or video to detect writing behavior, recent iterations are more sophisticated [8]. All this information aids educators to better accommodate at-risk pupils and enhance pedagogical approaches 11. Other machine learning techniques like SVM, decision trees, and LightGBM have proven to be effective in detecting behavioral anomalies 4. CNNs and LSTMs are two deep learning models that have been evaluated to enhance temporal activity recognition, as per the review by have been evaluated to enhance temporal activity recognition, as per the review by Gupta et al. [6], showing their effectiveness across sectors, including education.

Despite achievement in other areas such as healthcare and smart respectable things, HAR in relaxation chamber are vastly differing. The recognition should be accurate considering personal differences and preventing bias; thus, it needs a dataset diverse enough to reflect the real-life classroom actor's behaviors as KU-HAR [13].

Education on AI is one of the hottest areas right now. According to Martins and Von Wangenheim [7], teaching Artificial Intelligence through understanding the concepts in the early stages creates people with good analytical skills and responsible towards AI and Intelligent systems. Similarly, Fahd et al. [11] demonstrated how large-scale machine learning might be used to find at-risk students, reinforcing its value in academic monitoring. In conclusion, HAR and AI-driven monitoring hold great potential for enhancing education, but their use must ensure transparency, fairness, and student privacy.

1.1 Human Activity Recognition (HAR)in Education

In simple terms, Human Activity Recognition (HAR) is detecting human activity by classifying the input data coming from different sources like sensors, cameras or wearables. In these educational contexts, HAR is widely used to supervise student attention spans, note taking, and mobile device usage to improve classroom involvement and learning outcomes [1][6]. Recent advancements in Deep learning-based models have indicated their performance in improving the performance of HAR systems. Khatun et al. utilized a self-attention mechanism with wearable sensors, and Zhang et al. [8] created a hybrid CNN-LSTM that yielded beneficial results for accurately identifying different actions similarly. Cruciaini et al. [9] employed CNNs to process IMU and audio data, enhancing feature extraction for correct classification of activities. Vidya and Sasikumar [17] were one of the early works to apply the multi-sensor fusion in classroom contexts for reliable behavior detection. Ramanujan et al. a review was carried out on HAR systems which used smartphones and wearables, highlighting their importance for real-time monitoring within classrooms [10]. This is further supported by Alruwais and Zakariah [1], how HAR can help in identifying disengaged students and, helping and personalizing learning approaches.

1.2 Explainable AI Ethical Consideration in Student Monitoring

The education sector is capitalizing on AI as pilots become increasingly ubiquitous, creating essential ethical considerations, especially around privacy, transparency, and fairness. XAI is an indispensable part of educational AI systems as many stakeholders need to comprehend and trust any automated decisions about student conduct or academic performance (Dastani and Ahang [20].

Demidova et al. [4] highlighted the distinction between motivated and suspicious behaviors in students by creating anomaly detection models. Although these models are beneficial, it’s essential to consider the potential for misclassifications and to account for contextual variations. In a similar vein, Csizmadia et al.[19] used lightGBM to identify activities in children through wearable devices, achieving commendable accuracy while also raising issues related to excessive monitoring and data sensitivity. The risk of algorithmic bias and the potential misuse of data call for strict ethical standards. Furthermore, de Oliveira et al. [15] emphasized the necessity for both students and teachers to acquire knowledge regarding AI and advocated for clarity in algorithmic processes. Educational institutions must ensure that students understand how their data is utilized to safeguard their autonomy.

II. RELATED WORK

The domain of abbreviation of human activity recognition (HAR) has been developed as a key technology that can be used to build smart systems that can detect and classify human activities using sensor data, video input or biometric feedback. In this domain, however, the technology has been extensively utilized to monitor classroom activities as well as students’ attentiveness and behavioral patterns that impact learning outcomes. As technology becomes more integrated with education, many researchers have proposed many advanced methods to detect and analyze how students engage with mobile phones, sleep during lectures, and show signs of disengagement.

Alruwais and Zakariah invested significant effort into recognizing student engagement in real time by assessing posture and facial expressions. Their models apply deep learning methods to differentiate between active and passive learning in both face-to-face and online educational settings. Similarly, Brahim employed statistical metrics gathered from online platforms to forecast academic success, highlighting the importance of online behavioral patterns in understanding student motivation and performance. Advanced AI frameworks have been utilized to enhance the accuracy of behavior detection. Khatun et al. developed a hybrid model that combines CNN and LSTM, incorporating self-attention mechanisms that effectively recognized both static and dynamic activities through wearable sensors. Similarly, Cruciani et al. enhanced the precision of activity classification by combining IMU and audio data through CNN methods. These models have considerably contributed to the development of HAR systems, evolving from traditional gesture recognition to encompass more stable actions like head movements, micro-expressions, and changes in posture.

For instance, Vidya Sasikumar [17] presented multi-sensor fusion to enhance the reliability of complex behavior recognition in smart classrooms. This research confirmed that student behavior monitoring systems would be much more robust when accompanied by visual, audio, and motion sensor data. Ramanujam et al. [10] surveyed wearable and smartphone-based HAR approaches that can be directly applicable in educational settings, where non-intrusive monitoring is needed to allow natural circumstances in the classroom.

Simply put, the advent of strong deep learning technologies has also enabled the use of object detection models like YOLO (You Only Look Once) to observe items over time. YOLO's ability to process very quickly and accurately makes it suitable for detecting students in a classroom environment where we need to catch them using mobile phones or sleeping. Other tools, such as Mediapipe, have further reduced the complexity of detecting hand and facial point landmarks for gesture and posture analysis. Together, these tools make it possible to non-invasively reconstruct real-time brain dynamics and observe them without compromising classroom dynamics.

Explainable AI (XAI) and an ethics framework are another essential element of current works. As emphasized by Wong et al. [20], complex deep learning systems were shown to provide transparency and interpretability, meaning that educators can understand the classification of behavior based on reason.

A growing range of applications of AI in education also requires solid datasets. The KU-HAR dataset provides a solution for such phenomena, accommodating activities as they appear naturally, as proposed by Skider and Nahid [13]. This data set has been widely used for benchmarking activity recognition models for educational purposes. Similarly, Gupta et al. [6] reviewed evidence of HAR in other domains and illustrated how approaches commonly employed in healthcare and disease surveillance could be adapted for use in classrooms.

Moreover, research such as that conducted by Fahad et al. [11] and Martins and Von Wangenheim [7] emphasizes the importance of incorporating AI literacy into academic programs. Instruction on the workings of AI models and training students in the collaborative creation of monitoring systems promotes transparency and fosters trust and acceptance. Casal-Otero et al. [14] and de Oliveira et al. [15] emphasized the importance of responsible innovation, noting that the utilization of student data in technology-enhanced learning exemplifies a scenario where ethical considerations need to be weighed against advancements across different field environments.

SNO	Author	Algorithm	Evaluation Parameters	Comments
1	Alruwais & Zakariah [1]	Deep Learning (CNN, LTSM)	Accuracy, Engagement Metrics	Effective in identifying student engagement.
2	Alruwais & Zakariah [2]	Deep Learning (CNN, LTSM)	Recognition Rate	Supports online and traditional settings.
3	Brahim [3]	Statistical Analysis	Behavioural Prediction Accuracy	Links behaviour with academic performance.
4	Demidova et al. [4]	Anomaly Detection	Precision, Recall	Fair behaviour classification focus.
5	Fahad et al. [4]	Decision Trees, ML models	Prediction Accuracy	Identifies at-risk students.

6	Gupta et al.. [5]	CNN, LSTM	Recognition Accuracy	Comprehensive HAR review.
7	Martins & Von Wangenheim [7]	Educational AI Systems Review	Systematic Analysis	Highlights ML education impact.
8	Khatun et al. [8]	Hybrid CNN-LSTM with Attention	F1-score, Accuracy	Robust for dynamic activity detection.
9	Cruciami et al. [9]	CNN with IMU and Audio	Classification Accuracy	High accuracy with sensor fusion
10	Ramanujan et al. [10]	Wearables & Smartphone HAR	Practical Usability	Effective in classroom settings.

Table-1

III. METHODOLOGY

The proposed system is an AI-based automated monitoring framework aimed at tracking student behavior and attendance in classrooms through advanced computer vision and machine-acquisition techniques. This model combines attendance monitoring with the identification of inappropriate behavior, which is particularly beneficial in educational environments where surveillance technologies are becoming more prevalent. By utilizing various machine learning techniques, including YOLOv8 for detecting objects, MediaPipe for identifying hand and facial landmarks, and FaceNet/DLib for recognizing faces, the system can provide accurate real-time monitoring. All alerts are promptly sent to faculty members through the Twilio WhatsApp API, and a comprehensive report on student behavior is generated after each session. The subsequent subsections offer additional details about the system's architecture and its operational processes.

3.1 Gathering and Preprocessing of Input

The system processing begins with the collection of inputs through CCTV or IP cameras installed in classrooms. These cameras continuously capture the surroundings in high-definition video streams. The video is broken down into individual frames, usually at a frequency of 15 to 30 frames per second, which is necessary for real-time processing frame keeps uniform dimensions and resolution, employing fundamental filtering methods such as Gaussian blur and brightness normalization, carried out by the preprocessing unit. This phase is crucial to ensure that subsequent detection models operate effectively, regardless of fluctuations in lighting or camera disturbances. Face alignment is essential in the preprocessing phase, employing Dlib's facial landmark prediction model. Since students might face various directions while interacting with an agent, the recognition and landmark models rely on the locations of specific facial features like the eyes and mouth. To reduce the computational burden, temporal sampling can be applied, analyzing only one frame for every 5 to 10 frames.

3.2 Object Detection with YOLOv8

Data from October 2023: c objects that are related to classroom misconduct, such as mobile phones, food items, and hand placements over the mouth or face. This detection output has bounding boxes, class probabilities, and confidence scores. If a mobile phone has a confidence reading above a preset threshold (0.8, e.g.) and the object belongs within the bounding box, the activity is classified as mobile usage if an object appears close to the student's hand/face region [44]. A bag of snacks or food in hand elicits the “eating” alert, too, in a similar fashion.

YOLOv8 is mathematically trained on a composite loss function, as shown below:

$$LYOLO=\lambda 1Lcls+\lambda 2Lobj+\lambda 3Lbox$$

Where:

- Lcls: classification loss
- Lobj: objectness score loss
- Lbox: bounding box regression loss
- lambdaλ: balancing parameters

3.3 Landmark Detection of Face and Hand with Mediapipe

YOLOv8 is specialized for detecting moving objects, but behavior patterns need a deeper understanding based on facial expressions and hand gestures. And this is where MediaPipe come into play. Besides, MediaPipe is Google’s cross-platform framework that allows the detection of 468 facial landmarks and

21 hand landmarks. This ground-breaking system permits the behavior classifier to not only incorporate object presence, but also facial expression and gestures.

3.4 Face Net & Drib Face Recognition
A facial recognition module is also added into the architecture to attach the behavioral logs of students. This module has two steps: face detection and face verification. First, a Dlib HOG or CNN face detector gets the face from the frame. After this, face Net extracts the face of a dimension of 128, and a specific student is compared with a previously registered database using a Euclidean distance:

$$d\,(f1,\,f2) = \|f1 - f2\|2$$

Where f1 and f2 are the respective embedding of the detected face and the stored face. If it is below a threshold (e.g. 0.6), a match is declared and attendance logged for that student. In cases where, after several efforts, no match can be found, the student can be recorded as absent.
Moreover, this module enables a seamless, non-intrusive attendance log in [25], combined with the detection of student's behaviors.

3.5 Notification System with Twilio
WhatsApp API One of the most important parts of the proposed system are real-time alerts. As soon as inappropriate activity is detected and confirmed by differentiating over multiple frames (to eliminate false positives), the system uses the Twilio WhatsApp API to send structured notifications to either the class teacher or HOD Alerts, including:
- Name of the student
- Behavior that was identified
- Time it happened
- Classroom environment
Example notification:
"Alert: student 'Ravi Kumar' was seen using a mobile device during the 10:15 AM session in Room B-104."
This immediate feedback allows teachers to intervene, when necessary, thereby improving classroom management and student focus.

3.6 Generation of Behavior Report
Alongside real-time notifications, the system generates a detailed behavior report for every session. These reports, created after each presentation, include:
Attendance for each student
The frequency and type of behavioral incidents
The duration of each event
Optional snapshot evidence
This information is made accessible in a weekly or monthly summary through secure data storage.
This module assists school authorities, counselors, and parents in making administrative decisions. Over time, behavior patterns can be assessed to pinpoint ongoing issues and facilitate suitable interventions.

3.7 Explanation of System Architecture
Figure 2 shows the complete system architecture. They are chained into a pipeline where the first stages process video input and the final stages prepare data output (notifying and reporting). The architectural design guarantees real-time responsiveness by applying parallelism to detection and recognition modules. Modular design allows the tool to scale across classrooms

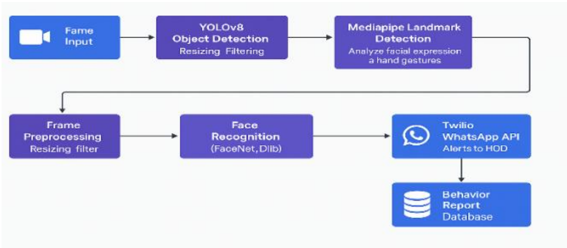


Figure 2. System Architecture of the proposed AI-Based Student Monitoring Framework

The architecture shows the modular interaction between video input, YOLOv8 object detection, MediaPipe gesture analysis, FaceNet-based identity recognition and Twilio-powered real-time alerts generation.

IV. RESULTS

To evaluate the effectiveness, reliability, and efficiency of the proposed AI-based student monitoring system, the experiment was performed in a real-world classroom. We provide a thorough description of the experiments performed, metrics used to measure performance, and comparisons of different algorithms applied towards behavior detection and attendance monitoring in this section.
Focus of results: You need to verify whether the object detection (YOLOv7, YOLOv8, EfficientDet) the facial recognition (FaceNet,Dlib) and gesture behavior identification can effectively work on the Android platform.

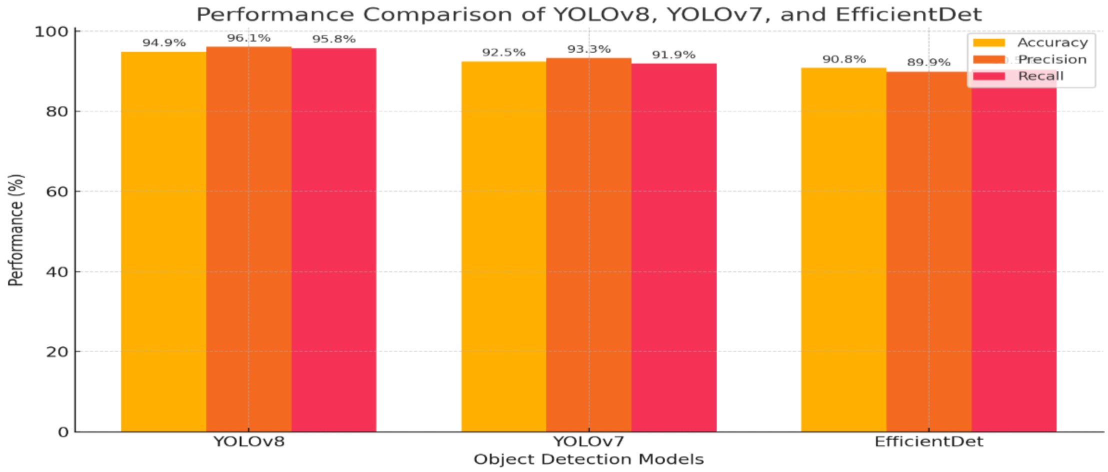
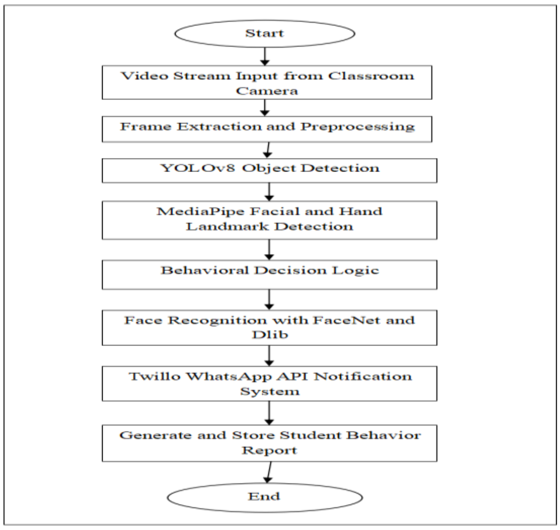


Figure 2: Performance Comparison of Object Models(YOLOv8, YOLOv7, EfficientDet)

Flowchart



4.1 Experimental setup

The system was tested in a smart classroom with 1080p IP cameras. Data was collected over 10 class sessions, each lasting around 45 minutes with an average of 25 students. 50h of videos were recorded and analyzed. To facilitate a supervised evaluation of detection accuracy, ground truth annotations were manually generated for each instance of mobile-phone use, sleeping and eating behavior.Testing was performed on the following hardware and software configurations:

TO do so, the authors make use of several tools, namely: Python 3.10, openCV, TensorFLow, PyTorch, Dlib and Twilio API

Models:

YOLOv8 (for object detection)

On the other hand, YOLOv7 and EfficientDet (for comparison)

Background (facial and hand landmarks) Mediapipe

FaceNet and dlib (for face recognition)

All of our models were trained and tested on a dataset as follows: for behavior detection we trained and tested on 3,000 annotated frames and for face recognition, we trained and tested with 500 unique student images.

4.2 Evaluation Metrics

Performance metrics for the evaluation of more models used the following performance metrics:

The proportion of true positives and true negatives over all instance types is called Accuracy (Acc):

Precision (P): No. Of true positives / (No. Of true positives + No. Of false positives)

Recall (R): True positives divided by the sum of true positives and false negatives

F1-score: Harmonic Mean of Precision and Recall.

Inference Time: Time taken per frame on average for the detection and classification process.

The formulas used are:

Accuracy = TP+TN/TP+TN+FP+FN Precision = TP/TP+TP+FN Recall = TP/TP+FN

F1 = 2(Precision * Recall/precision + Recall)

Where:

TP = True Positive

FP = False Positive

TN = True Negative

FN = False negative

4.3 YOLOv8 vs YOLOv7 vs EfficientDet Detection Results

The important task of identifying students who are using mobile phones, sleeping, or eating is done by the object detection module. We evaluated the detection accuracy, precision, recall, and F1 score of three state-of-the-art object detection models on the same dataset.

Table 1. Evaluation of object detection Models

As can be seen in Table 1, the detection accuracy, F1-score, and inference speed of YOLOv8 beat the other two models. The lightweight and optimized architecture of YOLOv8 makes it ideal for real-time monitoring it ideal for real-time monitoring of classrooms. With the least number of false positives in identifying behavioral events as well as the fastest average inference time, it can be deployed in time-sensitive environments such as classrooms.

Table 2: Performance Comparison of Object Detection Models

Model	Accuracy	Precision (%)	Recall (%)	F1-Score (%)	Avg. Inference Time (ms)
YOLOv8	94.87	96.10	94.01	94.01	28
YOLOv7	92.45	93.30	92.59	92.59	35
EffcientDet	90.82	89.94	90.19	90.10	52

Based on Table 2, YOLOv8 outperforms the other two models in terms of detection accuracy, F1-score, and inference speed. Its lightweight and optimized structure makes YOLOv8 ideal for real-time monitoring in classrooms. It effectively identified behavioral events while maintaining a lower incidence of false positives and achieved the fastest average inference time, which makes it highly appropriate for urgent situations like those in classrooms.

4.4 Graphical Comparison of Object Detection Models

Figure 1 demonstrates the performance measures, accuracy, precision, and recall of YOLOv8, YOLOv7, and EfficientDet. From the graph, it's evident that the performance of YOLOv8 exceeds other models across all three metrics. (p006) mAP scores of various algorithms and our proposed faster R-CNN (blue):x: EfficientDet (orange):x: YOLOv7 (yellow):x: the highest mAP of 94.87% was placed by our algorithm; secondly, the second spot (92.45% mAP score) was taken by YOLOv7, and after it 90.82% by the EfficientDet. The precision and recall values follow a similar pattern, confirming the applicability of YOLOv8 for real-time behavioral detection in a classroom environment. Inference time and detection accuracy tend to yield a wider gap between YOLOv8 and EfficientDet (as seen in fig.10), thus suggesting points towards the use of YOLOv8 in latency-sensitive educational applications.

4.5 Attendance Recognition Accuracy:

FaceNet vs Dlib FaceNet vs Dlib, Evaluating Reliability of Attendance tracking to evaluate the reliability of the attendance tracking, we tested the performance of two very popular face recognition models, FaceNet and Dlib, on the same dataset. 500 student face images were tested for each model, which were taken under different angles and lighting conditions. The accuracy, precision, recall and F1-score were computed against successful matches (face matched to a registered database entry).

Table 3: Performance Comparison: FaceNet vs Dlib

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Avg. Matching Time (ms)
FaceNet	96.45	97.10	95.89	96.49	42
Dlib	91.88	92.60	90.11	91.34	78

4.6 MediaPipe-Based Gesture

Detection Evaluation: Because behaviors such as sleeping and eating can be detected based on hand and facial gestures, we tested the MediaPipe framework for robustness in landmark tracking for both the face and hand. Thus,600 events (200 eye closure, 200 different eating gestures, and 200 hand-to-face movement at the beginning, midway and the end of the eating events) were annotated and utilized in the test. Detection outcomes were assessed as successful matches with ground truth observations. MediaPipe produced a high accuracy on all gesture types. The best detection rate was achieved with sleeping behavior identified by continuous eye-closure patterns. Mobile usage was a bit harder to detect, but the overall accuracy still hovered above 93% as there is only one gesture for that setup that would work. These results validate the use of MediaPipe for lightweight and real-time gesture-based tracking of student behavior.

Behavior Type	Detection Accuracy (%)	False Positive Rate (%)
Sleeping	94.2	3.55

Eating	91.70	4.89
Mobile Usage	93.10	3.11

Table 4: Gesture Accuracy Using MediaPipe

4.7 Output of the Proposed System

The suggested smart classroom monitoring system utilizing AI delivers various outputs aimed at automating behaviour recognition, creating immediate alerts, and assisting in precise attendance monitoring. These outputs enhance classroom management while also offering insights into student involvement through visual data and analytical reports.

Student Name	ID	Behaviour Detected	Time	Action Taken
B. Yashwanth	20CSE0345	Sleeping	10:10 AM	WhatsApp Alert Sent
E. Karthik Sai	20CSE0378	Mobile usage	10:23 AM	Logged in Report
C. Nikhil	20CSE0301	Eating	10:35 AM	No Alert (Minor)

Table5: Session-Based Behaviour Report

Figure3 : Real-Time WhatsApp Alert Notification

V. CONCLUSION

The proposed research developed and verified an AI student monitoring framework which merges computer vision systems with deep learning features alongside real-time communication protocols. Through the Twilio API the system generates immediate behaviors including mobile phone usage sleeping and eating. The combined use of Face Net and Dlib models delivered a system that performed both trustworthy and non-evasive student attendance tracking.

Universities are expected to experience enhanced classroom discipline outcomes and a decrease in educators' workloads through the suggested framework, which streamlines both behavior monitoring duties and reporting tasks. The behavior reports generated after class through this framework allow educational institutions to carry out long-term assessments of student engagement, aiding their decision-making processes. Future enhancements to this system will incorporate emotional detection features while also offering personalized suggestions and various camera perspectives for observation. This advancement in educational technology represents significant progress in classroom management practices, leveraging the capabilities of artificial intelligence.

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