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AI-Based Classroom Monitoring and Attendance System

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***Abstract*—This paper describes an artificial intelligent attendance system for education that includes behavioral tracking and distractions interruptions. Inadequate student attendance accounts derive from the limits of traditional roll call systems in measuring student engagement. This proposal integrates motion detection, sleep recognition, facial recognition, and mobile phone usage monitoring to provide real-time focus tracking of students. The system was implemented on a Raspberry Pi and uses OpenCV and machine learning for accurate behavior assessment and recognition. It also correlates students' engagement to the instructional activities being performed in the class to determine teacher effectiveness. The real-time monitoring of data allows the decision-makers and educators to target and improve the teaching approaches to better serve the student needs and outcomes. When traditional attendance monitoring is replaced by AI driven real-time classroom monitoring, attendance grows, learning achievements are reached, and distractions are minimized.**

Keywords—AI-Based Attendance, Face Recognition, Behavioral Monitoring, Student Engagement Analysis, Teacher Efficiency Evaluation, Phone Usage Detection, Sleep Detection in Classrooms, Real-Time Classroom Analytics, Automated Attendance System, Machine Learning in Education

I. INTRODUCTION

Active participation is a key factor in a student's academic success, influencing not only their performance but also their overall learning experience. However, traditional attendance systems—such as manual sign-in sheets or RFID-based tracking—only record physical presence and fail to measure a student's level of engagement [2]. A student might be physically present in class but mentally distracted, whether by using their phone, feeling drowsy, or simply not paying attention[15]. In large classrooms, where monitoring individual students is nearly impossible, ensuring attentiveness becomes even more difficult.

Current attendance tracking methods have notable limitations. Manual sign-ins are error-prone and time-consuming, while RFID or mobile-based systems can be easily manipulated through proxies[8]. Even digital solutions often struggle to scale effectively in larger classrooms. To address these challenges, this research introduces an AI-driven system that automates attendance tracking while also monitoring student engagement in real time[4].

The system leverages facial recognition, behavioral tracking, and object detection to analyze classroom interactions beyond mere attendance[5]. It identifies key patterns, such as phone usage and drowsiness, providing educators with deeper insights into student engagement. For instance, if the system detects frequent phone use or signs of sleepiness, it could indicate issues beyond student distraction—such as ineffective teaching methods or unengaging lecture content. This enables institutions to take data-driven steps to enhance both student participation and teaching effectiveness.

Built using Raspberry Pi, OpenCV, and deep learning models, the system offers a cost-effective and scalable solution[7]. The camera module captures real-time video, processes facial and behavioral data, and logs critical insights such as entry and exit times, attentiveness levels, and distractions. Additionally, it provides real-time alerts and securely stores behavioral data for future analysis.

A unique feature of the system is its ability to assess classroom dynamics from both student and teacher perspectives. For example, if multiple students in a class show signs of disengagement (eg: using mobiles, etc)it may indicate issues with teaching methods, classroom management or student disinterest. By identifying these trends, the system empowers educators to adjust their approaches, making learning more interactive and engaging. It also takes into account the behavioural changes made by the students and educators due to being monitored by a camera as well as other problems such as Neurodevelopmental disorders like Autism and ADHD[33][35][34].While factors such as ADHD or Autism may influence engagement, this study focuses on quantifiable variables such as phone usage and drowsiness, as subjective cognitive states are difficult to measure accurately.

Inspired by workplace monitoring tools like DigiSME and We360.ai, this project adapts similar principles for the education sector, incorporating features such as sleep tracking, phone usage detection, and motion analysis to deliver meaningful, actionable insights.

Ultimately, this AI-powered system aims to create a structured, engaging, and effective learning environment. By eliminating the inefficiencies of manual attendance tracking, providing real-time behavioral insights, and helping educators refine their teaching methods, this project has the potential to revolutionize classroom management and enhance overall educational outcomes.

II. LITERATURE REVIEW

A. Introduction

Facial recognition technology, a subset of artificial intelligence (AI), has advanced significantly over the past two decades. Its application in automated attendance systems has gained traction in educational and corporate settings due to its efficiency and non-intrusiveness[10]. Early automated attendance methods, such as punch cards, magnetic stripe cards, barcodes, and RFID systems, faced challenges that hindered seamless tracking. With AI's progression, researchers have sought more reliable solutions for accurate attendance recording. Beyond attendance, AI-driven behavioral tracking has the potential to provide insights into student engagement, classroom effectiveness, and even teacher efficiency.

B. Face Detection and Recognition Algorithms

- *Haar Cascade Classifier*

Introduced by Viola and Jones in 2001[6], the Haar Cascade classifier marked a milestone in real-time face detection. Studies have implemented this classifier in attendance systems, especially in resource-constrained environments like the Raspberry Pi[13]. Its lightweight nature and low computational requirements make it suitable for such applications. However, limitations arise in handling varied facial angles, poor lighting, or partial occlusions, leading to decreased accuracy.

- *Deep Learning-Based Face Detection*

Deep learning models, notably FaceNet, have revolutionized face recognition by employing deep convolutional networks to generate precise face embeddings[9]. Research indicates that integrating FaceNet and Dlib into attendance systems enhances accuracy compared to traditional methods. Nonetheless, these models demand substantial computational resources, posing challenges for real-time applications on devices like the Raspberry Pi without optimizations such as TensorFlow Lite.

C. OpenCV for Image Processing

OpenCV, a widely used library, is instrumental in face detection and recognition tasks. It offers a range of pre-trained models, including Haar Cascades, and supports deep learning models like FaceNet through its DNN modules. Studies highlight OpenCV's seamless integration with platforms like the Raspberry Pi, making it a preferred choice for developing cost-effective face recognition systems for attendance tracking[4]. Its flexibility and user-friendly interface have solidified its role in such projects.

D. Hardware Considerations for Face Recognition Systems

- *Raspberry Pi as a Cost-Effective Option*

Researchers have explored the Raspberry Pi's viability for face recognition attendance systems, citing its affordability and accessibility[8]. This makes it an attractive option for implementing AI applications in educational institutions and small businesses where budget constraints exist, yet efficient attendance tracking is essential.

- *Hardware Limitations and Alternatives*

Despite its cost benefits, the Raspberry Pi's limited processing power presents challenges in running complex face recognition models in real-time[7]. Studies have noted issues with frame rates and handling large datasets. Consequently, developers often opt for lightweight models like Haar Cascades, which, while compatible with the Raspberry Pi, may not offer the accuracy of more advanced models. Alternatives such as Jetson Nano, Coral Edge TPU, and cloud-based processing have been explored for enhanced computational efficiency, but cost and infrastructure requirements remain key considerations.

E. Accuracy, Challenges, and Ethical Considerations

- *Accuracy and Real-World Challenges*

Comparative studies of face detection and recognition algorithms in real-world scenarios reveal that deep learning models generally surpass traditional methods[11]. However, challenges persist with environmental factors such as inadequate lighting and partial occlusions, which remain significant obstacles, particularly when scaling systems for broader applications. Additionally, integrating behavioral tracking for classroom engagement monitoring introduces complexities in data interpretation.

- *Ethical and Privacy Implications*

The deployment of facial recognition technology in attendance systems raises critical ethical and privacy concerns[26]. Scholars have highlighted potential risks, including misuse and data breaches. To mitigate these issues, there is a call for stringent data protection regulations and the adoption of privacy-preserving techniques, such as federated learning and encrypted data storage, to safeguard individual information within face recognition systems.

F. PsychoSocial Aspect of student and teacher engagement.

A key aspect in evaluating the student and teacher behaviour towards the class under the surveillance of the camera can be attributed to the Hawthorne effect. While the original research on the Hawthorne effect had broader implications than initially intended, it remains influential in understanding behavioral changes under observation.[33]. Being monitored by the camera and then being evaluated leads both the teacher and students to display behaviours that would otherwise be outside their usual self. Another aspect to consider are the Neurodevelopmental disorders in students. NDD's like ADHD and Autism are usually common. According to the World Health Organisation(WHO), 5% of children and 2.5% of adults have ADHD[34] and according to the American Association of Pediatrics, 1 in 36 kids have Autism[35]. This poses a challenge for educators to track their behavior, thus indicating that a student not focusing in class is not necessarily the educators fault or the students disinterest in said subject.

G. Behavioral Analysis for Teacher Efficiency Evaluation

In addition to tracking student attendance and engagement, the proposed system introduces a methodology to evaluate teacher effectiveness based on student behavioral patterns[16]. The system continuously monitors factors such as:

a. Student Engagement: Percentage of students actively engaged during the session.
b. Distractions: Percentage of students distracted (e.g., phone usage or drowsiness).
c. Attendance Consistency: Ratio of students who attended consistently during the lecture.
d. Behavioral Trends: Patterns of student disengagement (e.g., frequent drowsiness or inattentiveness).

- Teacher Efficiency Calculation:

A formula is introduced to quantify teacher efficiency as a percentage:

Teacher Efficiency (%) = (W1·E+W2·(1−D) + W3·A) × 100\text {Teacher Efficiency (\%)} = \left(W_1 \cdot E + W_2 \cdot (1 - D) + W_3 \cdot A \right) \times 100

Where:

- EE: Engagement Level (e.g., % of students actively engaged).
- DD: Distraction Level (e.g., % of students using phones or sleeping).
- AA: Attendance Consistency (e.g., % of students present for the entire session).
- W1,W2,W3W_1, W_2, W_3: Weights for each factor based on importance (e.g., W1=0.5,W2=0.3,W3=0.2W_1 = 0.5, W_2 = 0.3, W_3 = 0.2).

H. Conclusion

While AI-driven facial recognition offers promising advancements for automated attendance systems, careful consideration of technical limitations and ethical implications is imperative to ensure effective and responsible implementation. The integration of behavioral tracking and teacher efficiency analysis provides a holistic approach to classroom monitoring, fostering both improved student engagement and enhanced teaching strategies.

III. PROPOSED SYSTEM

A. System Overview

The AI-powered attendance and behavior tracking system boosts classroom participation analysis. It does this by making attendance checks automatic while also checking how attentive students are and how well teachers perform[11]. This system is different from old-school attendance setups that use face recognition. Instead, it brings together movement tracking, sleep spotting, phone use watching, and involvement analysis to give a fuller picture of what's happening in class[12].

This system uses OpenCV deep learning setups, and behavior tracking methods to work through live video feeds spotting patterns in how students act. For the hardware, it uses a Raspberry Pi (or something like it) hooked up to a camera. This lets it process stuff right there with very little delay. This setup means it can do quick real-time analysis without needing a lot of cloud computing making it easy to scale up and not too pricey.

The system stores all data in a structured database giving administrators the ability to look at past engagement patterns and evaluate how well the teaching works. Also, it offers immediate feedback, which helps teachers change their methods based on how attentive students are.

By combining immediate logging, behavior analysis, and movement tracking, this setup serves as a clever way to monitor classrooms. It's a good fit for schools, company training programs, and research settings.

B. Features

1. *Haar Cascade Classifier*
   a. The system employs a hybrid approach combining Haar Cascade, FaceNet, and Dlib for high-accuracy face recognition[9].
   b. The camera records live video feeds, which are processed to:
      - Detect and recognize individual students.
      - Assign timestamps and log attendance automatically.
      - Prevent proxy attendance by using motion detection to distinguish between live individuals and printed photos or static images.
      - Identify patterns in student engagement, correlating attendance with attentiveness.
2. *Phone Usage Detection*
   a. A CNN-based object detection model identifies smartphone usage in real time[17].
   b. The system logs timestamps when phone usage is detected, flagging students as distracted.
   c. Educators receive reports on frequent phone usage, helping them address distractions effectively.
   d. Insights from phone usage patterns contribute to teacher efficiency analysis, highlighting lectures that may need improvement.
3. *Sleep Detection and Behavioral Monitoring*
   a. The system analyzes eye movement, head posture, and motion data to detect drowsiness in students[30].
   b. A combination of facial recognition and behavioral tracking identifies closed eyes, nodding heads, and inactive postures.
   c. Sleep detection is correlated with lecture engagement, allowing teachers to adjust instructional strategies.
   d. The system logs instances of disengagement, helping administrators review student focus levels over time.
4. *Motion Analysis for Classroom Engagement*
   a. Using motion tracking algorithms, the system differentiates active participation from passive presence[29].
   b. The model detects students moving in and out of the classroom, logging entry and exit times automatically.
   c. Continuous analysis of body posture and responsiveness provides insights into overall class attentiveness.

5. *Teacher Efficiency Evaluation*

The proposed system extends beyond monitoring student behavior by introducing a data-driven framework for evaluating teacher effectiveness. By analyzing classroom engagement patterns, it provides actionable insights that help educators and administrators refine their teaching strategies[16].

Teacher efficiency is quantified using a weighted formula that takes into account three key metrics:

Teacher Efficiency (%) = (W1·E+W2·(1−D) + W3·A) × 100\text {Teacher Efficiency (\%)} = \left(W_1 \cdot E + W_2 \cdot (1 - D) + W_3 \cdot A \right) \times 100

Where:

- EE (Engagement Level): Percentage of students actively participating in the class.

- DD (Distraction Level): Percentage of students showing inattentiveness, such as phone usage or signs of drowsiness.
- AA (Attendance Consistency): Percentage of students present for the entire session.
- W1,W2,W3W_1, W_2, W_3: Weighted factors assigned based on importance. A possible weight distribution could be W1=0.5W_1 = 0.5, W2=0.3W_2 = 0.3, and W3=0.2W_3 = 0.2, prioritizing engagement as the most critical factor.

This quantifiable measure of teacher performance allows for an objective assessment of instructional effectiveness.

For example:

- A class with low engagement and high distraction rates may indicate ineffective teaching strategies, requiring adjustments in content delivery or classroom management.
- Conversely, high engagement and consistent attendance suggest effective instruction and a productive learning environment.

By providing real-time feedback, the system empowers educators to identify areas for improvement, adapt their teaching methods, and foster a more dynamic and interactive classroom.

Administrators can also leverage this data for professional development initiatives, ensuring that teaching strategies evolve in response to the changing needs of students.

- Impact on Education

This evaluation framework creates a feedback loop that benefits both educators and learners. By bridging the gap between student behavior and teaching effectiveness, it supports data-driven decision-making in education, paving the way for improved teaching methodologies and better student engagement outcomes.

6. Real-Time Logging and Data Storage

The system incorporates real-time logging to systematically record attendance, engagement levels, and behavioral insights[27]. All captured data is stored in a structured database, ensuring efficient data management and easy accessibility for analysis.

Key Logged Data Points:

a. Entry and Exit Times: Automatically records when a student enters or leaves the classroom.
b. Engagement Levels: Logs student attentiveness based on facial recognition and motion tracking.
c. Distraction Patterns: Detects and logs instances of phone usage, sleeping, or lack of movement during lectures.
d. Cumulative Behavioral Trends: Tracks long-term student engagement patterns to identify habitual distractions or learning challenges.

Accessibility and Reporting

a. Administrators and teachers can access detailed real-time and historical reports.
b. The dashboard interface presents visual analytics, making it easier to interpret student engagement and behavioral trends.
c. The system can generate summaries for individual students, entire classes, or institution-wide participation trends.

By storing and analyzing this data over time, institutions can make informed decisions about student learning patterns, classroom effectiveness, and areas that need pedagogical improvements.

IV. METHODOLOGY

A. Hardware Setup

The system is designed to operate efficiently using a combination of embedded hardware and AI-driven software. The key hardware components include:

a. Raspberry Pi 4: Serves as the primary processing unit, handling data input, real-time video analysis, and AI model execution.
b. Camera Module: Captures live video feeds for facial recognition and behavioral analysis.
c. Optional Sensors: Additional motion sensors can be integrated to enhance engagement tracking and detect physical movement patterns in the classroom.

B. Software Architecture

1. Operating System

- Raspbian OS: A lightweight and optimized Linux-based operating system tailored for Raspberry Pi, ensuring system stability and efficiency.

2. Programming Language and Libraries

- Python: The primary programming language for system scripting and development.

- OpenCV: Used for image processing, face detection, and behavioral tracking.
- NumPy: Supports numerical operations essential for handling image processing tasks.
- TensorFlow/Keras: Deep learning frameworks employed for facial recognition, phone usage detection, and behavioral analysis.
- Flask: Provides a web-based user interface to facilitate attendance tracking, behavioral analysis, and real-time analytics for educators and administrators.

C. Data Logging and Storage

1. Types of Data Logged

The system collects and organizes a variety of data points to generate insights into student behavior and classroom engagement:

- Attendance Records: Captures names and timestamps marking student entry and exit.
- Motion Events: Logs the time and duration of detected motion, indicating student activity levels.
- Behavioral Metrics: Records instances of distractions, such as phone usage, sleep detection, and engagement levels.

2. Storage Solutions

The system employs both local and structured storage solutions to manage recorded data efficiently:

- SQLite Database: Stores attendance records and behavioral data locally on the Raspberry Pi, ensuring quick access and efficient data retrieval.
- File-Based Logging: Data can be exported in CSV or JSON formats, allowing for external analysis and long-term trend monitoring.

D. Implementation Process

- Data Capture: Each recognized face is logged with a timestamp, ensuring accurate attendance tracking.
- Motion Detection Logging: Movement data is recorded to analyze classroom engagement and participation levels.
- Periodic Updates: Attendance and behavioral records are updated continuously, ensuring real-time monitoring and comprehensive data analysis.
- User Interface (UI): A Flask-based dashboard provides a structured and user-friendly interface, allowing teachers and administrators to view attendance records, student engagement trends, and behavioral insights in real time.

V. RESULTS AND DISCUSSION

A. Accuracy of Face Recognition

The system's FaceNet model demonstrated high accuracy in recognizing student faces under different conditions[18]:

a. Achieved 95% accuracy in controlled environments with optimal lighting and clear facial visibility.
b. Accuracy dropped to 85% in varied lighting conditions or when faces were partially occluded.
c. False positives were minimized by implementing a voting system, which required consecutive frame matching before confirming an identity.

B. Phone Usage Detection

The CNN-based phone detection model successfully identified instances of phone usage, contributing to distraction analysis[17]:

a. Attained 90% accuracy in detecting phone usage based on hand movements and head posture.
b. False positives mainly occurred due to unrelated hand movements, such as adjusting glasses or scratching the face.
c. The model performed best when trained with a diverse dataset covering different phone positions and lighting conditions.

C. Sleep Detection

The eye-tracking model effectively detected drowsiness and sleep behavior in students[30]:

a. Achieved 80% accuracy in identifying closed eyes and signs of fatigue.
b. The system analyzed factors like eye closure duration, head tilting, and motion inactivity to improve reliability.
c. Adjusting the eye closure threshold helped reduce false positives caused by slow blinking or momentary eye rest.

D. System Performance

The system was evaluated for its efficiency in real-time classroom monitoring[15]:

a. Face recognition response time: Under 2 seconds per detection cycle.
b. Phone usage and behavioral tracking delay: Approximately 2-3 seconds, ensuring near real-time performance.
c. The model was optimized for edge computing using a Raspberry Pi,

maintaining consistent frame rates and processing efficiency without excessive computational demand.

VI. CONCLUSION

In conclusion, this paper presents an advanced AI-based attendance system that integrates face recognition with phone usage detection and sleep monitoring. Utilizing Raspberry Pi, OpenCV, and deep learning models, this system offers a highly efficient and practical solution for real-time attendance tracking and behavioral analysis. By leveraging Haar Cascade for initial face detection and incorporating FaceNet for precise recognition, the system ensures accurate identification while maintaining detailed behavioral logs for comprehensive student monitoring[29].

This solution provides real-time insights into student engagement and distractions, making it an essential tool for educators seeking to improve classroom participation. Future enhancements will focus on refining phone usage detection under diverse conditions, integrating additional behavioral cues such as emotional engagement, and expanding system scalability for larger classrooms[26].

While factors like camera quality, lighting conditions, and environmental variables may impact face recognition accuracy, these challenges can be mitigated through system optimization and adaptive improvements. Overall, this project presents a cost-effective, scalable approach to automated attendance tracking and classroom behavior monitoring, making it a valuable asset for educational institutions, corporate training environments, and beyond.

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