EDUCAM AI: SMART EVENT DRIVEN CLASSROOM MONITORING & REAL TIME ALERTS

A PROJECT REPORT

Submitted by

FIAZ KHAN A (411721106019)
KARTHIKEYAN S (411721106034)

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ANNA UNIVERSITY : CHENNAI 600 025

BONAFIDE CERTIFICATE

Certified that this project report **"EDUCAM AI: SMART EVENT DRIVEN CLASSROOM MONITORING & REAL TIME ALERTS"** is the Bonafide work of "**FIAZ KHAN A (411721106019), KARTHIKEYAN S (411721106034)",** who carried out the project work under my supervision.

SIGNATURE	**SIGNATURE**
Dr. K. K. SENTHIL KUMAR, M.E., Ph.D.,	Mrs. RAMYA. M.S, M.E., MBA
	Assistant Professor
HEAD OF THE DEPARTMENT	**SUPERVISOR**
Department of Electronics and Communication Engineering Prince Shri Venkateshwara Padmavathy Engineering College, Chennai-127	Department of Electronics and Communication Engineering Prince Shri Venkateshwara Padmavathy Engineering College, Chennai-127

Submitted for viva-voce held on ____________

INTERNAL EXAMINER **EXTERNAL EXAMINER**

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ABSTRACT

EduCam AI is a smart classroom solution that enhances classroom management and safety using AI-driven technologies. It employs H.265 IP cameras with polarization lenses and a Raspberry Pi for event-based video processing, reducing operational costs and improving ROI. The system uses Face Recognition and OpenCV to automate attendance, logging data directly to Google Sheets Integration. The EduCam AI Bot delivers real-time alerts via SMS and Telegram for attendance, motion detection, and safety events. Gesture recognition allows students to raise virtual requests (like a raised hand), while animal detection algorithms help ensure campus safety. This efficient, scalable model reduces computational load and eliminates the need for continuous surveillance, making it ideal for modern educational environments.

Keywords: EduCam AI Bot, Smart Classroom, Face Recognition, OpenCV, Gesture Recognition, Google Sheets Integration, ROI, Animal Detection, Real-Time Alerts

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LIST OF ABBREVIATIONS AND SYMBOLS

AI	-	Artificial Intelligence
ROI	-	Region of Interest
HOG	-	Histogram of Oriented Gradient
YOLO	-	You Only Look Once
API	-	Application Programming Interface
IP	-	Internet Protocol
NVR	-	Network Video Recorder
GSM	-	Global System for Mobile Communication
SSH	-	Secure Shell
VNC	-	Virtual Network Computing
CSV	-	Comma Separated
H.264	-	High Efficiency Video Coding
USB	-	Universal Serial Bus
CNN	-	Convolutional Neural Network
UDP	-	User Datagram Protocol
MQTT	-	Message Queuing Telemetry
MTCNN	-	Multi-Task Cascaded Convolutional Networks
GUI	-	Graphical User Interface
Dlib	-	Data Library(Machine Learning Toolkit)

CHAPTER 1
INTRODUCTION

The rapid evolution of digital technology has significantly transformed various aspects of modern life, from personal communication to large-scale industrial processes. In educational settings, the drive to improve operational efficiency, enhance security, and provide real-time information has led to the integration of advanced surveillance and monitoring systems. This report presents Educam AI: Smart Event-Driven Classroom Monitoring & Real-Time Alerts, an innovative solution designed to automate attendance tracking and enhance classroom safety by harnessing state-of-the-art artificial intelligence (AI) techniques and cost-effective hardware. In this introduction, we discuss the background and motivation behind the project, present a detailed history and evolution of CCTV surveillance technology, articulate the problem statement and project objectives, and provide an overview of the report's organization.

1.1 BACKGROUND AND MOTIVATION

Educational institutions worldwide are continually seeking ways to streamline administrative processes, optimize resource allocation, and ensure the safety of students and staff. Traditional methods of classroom management such as manual attendance, physical roll calls, or even biometric systems like fingerprint scanning present numerous challenges. They are labour intensive, prone to human error, and often fail to provide real time data that is crucial for prompt decision-making in dynamic environments. In addition to the inefficiencies in attendance management, continuous surveillance has become essential for maintaining security and monitoring the overall environment. However, conventional video surveillance systems typically rely on constant, uninterrupted video streaming and processing, which places a heavy burden on computational resources, increases power consumption, and leads to bandwidth congestion. These systems are often 4 expensive to implement and maintain, especially in institutions where budget constraints are a critical concern.

Recent advancements in AI and machine learning have paved the way for smarter, more efficient monitoring systems. These systems can now process data selectively triggering analyses only when significant events occur thus conserving resources while still providing accurate and timely information. With the advent of cost-effective platforms like the Raspberry Pi and the integration of robust AI frameworks such as face_recoginition, it is now feasible to design systems that are both scalable and economical without sacrificing performance. The development of Educam AI is driven by the increasing need for efficient, automated, and intelligent surveillance systems in educational institutions. Traditional methods of attendance tracking, such as manual roll calls, biometric scanners, or RFID based systems, are often time-consuming, error-prone, and susceptible to misuse.

Additionally, ensuring security within classrooms and academic premises remains a significant challenge due to the limitations of conventional CCTV systems, which rely heavily on human supervision for monitoring activities. To address these challenges, Educam AI integrates a multi-functional surveillance and attendance system that leverages the power of event-driven processing, selective video data analysis, and real-time alert mechanisms. By employing intelligent video analytics, the system automates the attendance marking process, eliminating the need for manual intervention. This not only enhances accuracy but also prevents issues like proxy attendance. Beyond attendance tracking, Educam AI significantly enhances classroom security by continuously monitoring for unusual activities and triggering alerts for potential threats. The system is designed to detect unauthorized entry, security breaches, and potential hazards. Upon identifying any such anomaly, instant notifications are sent to faculty members, security personnel, or administrative staff, ensuring quick response and mitigation of risks. A key advantage of Educam AI is its reliance on affordable hardware solutions such as IP cameras, Raspberry Pi, and Software such as Educam AI Bot using API, which significantly reduce implementation costs compared to expensive enterprise-level surveillance systems. The incorporation of AI-powered image processing and motion detection algorithms ensures optimal resource utilization by analysing only relevant video data instead of processing continuous surveillance footage. This minimizes bandwidth usage, reduces computational load, and optimizes energy consumption, making the system both cost-effective and scalable. By combining cutting-edge AI with real-time monitoring capabilities, Educam AI not only automates attendance tracking but also ensures a secure and controlled learning environment. The system's intelligent event-driven approach transforms traditional classroom monitoring into a proactive, data-driven solution, enhancing both operational efficiency and student safety.

1.2 HISTORICAL OVERVIEW OF CCTV SURVEILLANCE AND ITS EVOLUTION

The evolution of CCTV surveillance has undergone significant transformations over the past decades, advancing from rudimentary analog systems to intelligent, AI-driven surveillance solutions. The integration of digital technologies, networked IP-based cameras, and machine learning analytics has played a pivotal role in reshaping surveillance applications, particularly in educational institutions. This section outlines the key stages of development in CCTV technology and its impact on classroom security and automation.

1.2.1 Early Developments

The concept of closed-circuit television (CCTV) emerged in the mid-20th century as a novel method of visual surveillance. Early CCTV systems were primarily analog, using 6 bulky cameras and simple recording devices. Initially, these systems found application in military installations, government buildings, and industrial facilities where monitoring was essential for security and operational control. The primary advantage of these early systems was the ability to monitor remote or hazardous locations without exposing personnel to danger. During the 1960s, CCTV technology began to gain traction in urban environments. Law enforcement agencies, for instance, started deploying cameras in public spaces such as transportation hubs and high-crime areas. Despite the rudimentary quality of the images and the limitations of analog transmission, these early systems laid the groundwork for future advancements in video surveillance. Over time, businesses and private institutions also began adopting CCTV for theft prevention and employee monitoring. The growing demand for enhanced security led to continuous improvements in camera resolution and recording capabilities.

1.2.2 Transition to digital systems

The 1980s and 1990s witnessed a significant transformation in surveillance technology with the advent of digital video systems. Digital cameras, which offered improved resolution and image quality, began replacing analog cameras. This period also saw the introduction of digital video recorders (DVRs), which allowed for the storage, retrieval, and playback of video footage. The digital conversion marked a crucial milestone, as it facilitated more efficient data handling, easier integration with computer systems, and enhanced reliability in surveillance operations. During this time, video compression standards such as

MPEG-1 and later MPEG-4 were developed, enabling the efficient transmission of digital video over limited bandwidth connections. These innovations reduced the cost of storage and made it feasible to implement large-scale surveillance systems in public and private sectors. The move from analog to digital was also instrumental in improving the scalability of surveillance systems, as digital signals could be easily integrated into networked environments. Additionally, digital systems enabled remote monitoring capabilities, allowing real-time access from different locations. This flexibility greatly contributed to the widespread adoption of CCTV in commercial and educational settings.

1.2.3 The Internet Era and IP-Based Surveillance

With the widespread adoption of the internet in the late 1990s and early 2000s, surveillance technology underwent another major revolution. Internet Protocol (IP) cameras emerged as a breakthrough technology, allowing video data to be transmitted over computer networks. IP-based surveillance offered several advantages over traditional analog systems, including higher resolution, the ability to integrate with other networked systems, and remote accessibility. The use of IP cameras significantly enhanced the flexibility and scalability of surveillance systems, making them accessible to a broader range of users, including educational institutions.

The introduction of high-efficiency video coding (HEVC/H.265) further optimised the performance of IP cameras. This compression standard allowed for the transmission of high-quality video with reduced bandwidth consumption, making it ideal for real-time surveillance applications.

As educational institutions began to recognise the potential of these technologies, IP-based CCTV systems were increasingly adopted for both security and administrative purposes, such as monitoring classroom activities and managing attendance.

1.2.4 Integration with advanced analytics

The most recent phase in the evolution of CCTV surveillance is marked by the integration of advanced analytics and AI-based technologies. Traditional surveillance systems relied on human operators to monitor video feeds a process that was both labor intensive and prone to error. Today, intelligent video analytics have transformed how surveillance data is processed and interpreted. Machine learning algorithms, particularly those based on deep learning, can automatically analyse video feeds to detect faces, recognize objects, and even interpret human behaviour in real time. In the context of educational institutions, the integration of facial recognition has enabled the development of automated attendance systems. These systems leverage AI to accurately identify students based on facial features, significantly reducing the manual effort required for attendance marking. Moreover, event-driven processing techniques allow systems to focus on analysing data only when specific events occur such as motion in designated areas, thereby conserving computational resources and reducing energy consumption.

1.2.5 Modern trends and Future directions

Modern surveillance systems are increasingly characterised by their ability to integrate with cloud computing, the Internet of Things (IOT), and mobile communication networks. For instance, cloud-based storage and analytics enable centralised management of vast amounts of surveillance data, while IOT devices facilitate seamless connectivity between cameras, sensors, and processing units. In the educational sector, there is a growing trend toward the adoption of intelligent monitoring systems that not only ensure security but also enhance operational efficiency. The push toward automation, real-time data analysis, and remote accessibility is driving innovations that make surveillance systems more versatile and cost-effective.

Educam AI embodies this trend by combining selective, event-driven processing with AI-based analytics to deliver a smart classroom monitoring solution that addresses both attendance and security concerns. Future surveillance technology will focus on advanced AI models, biometric integration, and edge computing to enhance responsiveness and reduce latency, reshaping educational institutions' security management and paving the way for smarter, interconnected systems. The integration of cloud-based analytics will further enable real time monitoring and data-driven decision-making.

1.3 PROBLEM STATEMENT

Despite significant advances in surveillance technology, many existing classroom monitoring systems remain inefficient and cost-prohibitive. The following challenges have been identified:

1. High-End Hardware Dependence

Many contemporary systems require continuous processing using high end processors and GPUs to handle real-time video analytics. This reliance on expensive hardware not only increases the initial investment but also drives up energy consumption and maintenance costs.

2. Inefficient Continuous Processing

Conventional surveillance systems continuously stream and process video data regardless of whether significant events occur. This results in excessive use of bandwidth, high computational loads, and unnecessary energy consumption, ultimately making the system less scalable and more expensive.

3. Bandwidth and Storage Constraints

Continuous video streaming generates large volumes of data, which can overwhelm network bandwidth and require substantial storage capacity. This not only slows down data transmission but also complicates the retrieval and analysis of relevant footage.

4. Limited Real-Time Responsiveness

Systems that rely on continuous monitoring often face delays in processing, which can hinder real-time responsiveness. In scenarios where immediate action is required (e.g., detecting an unauthorized entry or a fire hazard), these delays can have serious consequences.

5. Integration of Multiple Functionalities

Existing systems often focus solely on attendance tracking or security surveillance. However, the modern classroom demands a multifunctional system that can handle attendance, security, and additional event-driven notifications without significant resource overhead. Educam AI addresses these issues by employing an event-driven, selective processing approach that minimizes continuous data handling. The system uses affordable hardware to perform AI-based facial recognition and event detection only when necessary, thereby reducing both the computational burden and the operational cost.

1.4 OBJECTIVES

The Educam AI project is designed to enhance classroom efficiency and safety through smart automation. Its core objectives include automating student attendance using AI-powered face recognition, implementing event-driven video processing to reduce unnecessary resource use, and improving classroom security via real-time anomaly detection. The system utilizes affordable hardware like Raspberry Pi to ensure cost-effectiveness while maintaining high performance.

1. Automate Attendance

Develop a robust AI-based system that accurately recognizes student faces during predefined time slots, automatically logging attendance in real time. This objective aims to reduce manual intervention and eliminate the inefficiencies associated with traditional attendance methods.

2. Implement Event-Driven Processing

Utilize motion detection to trigger video processing only when significant events occur (e.g., movement in critical areas). This selective processing approach aims to reduce unnecessary data handling, minimize bandwidth consumption, and lower the computational load on the processing hardware.

3. Enhance Classroom Security

Integrate additional event detection modules to monitor for anomalies such as unauthorized entry, potential fire hazards, or unusual activity. The system will provide immediate alerts to faculty and administrators through a API-based notification mechanism, thereby ensuring prompt responses to security incidents.

4. Optimize Cost and Resource Utilization

Leverage affordable hardware components, such as the Raspberry Pi, to build a cost-effective yet scalable system. By reducing the reliance on high-end processors and continuous processing, the solution aims to achieve significant savings in energy and operational costs while maintaining high performance.

5. Ensure Data Integration and Accessibility

Use the Google Sheets API to automatically update attendance records and maintain a centralized, cloud-based database. This integration not only streamlines data management but also provides easy access to historical data for analysis and reporting purposes.

6. Improve Video Quality Under Challenging Conditions

Enhance the performance of IP cameras by integrating polarization lenses to minimize glare and reflections.

1.5 THESIS ORGANIZATION

This report is structured to provide a comprehensive overview of the Educam AI project, covering all aspects from system design to performance evaluation. Chapter 1 introduces the project by detailing the background, motivation, problem statement, objectives, and the overall structure of the report. It sets the context and justifies the need for a more efficient and cost-effective classroom monitoring system.

Chapter 2 presents a thorough literature survey, reviewing existing classroom monitoring systems, facial recognition technologies, and event-driven surveillance methods. It identifies the limitations of current solutions and outlines the technological gaps that the Educam AI project aims to address.

Chapter 3 discusses the proposed system architecture in depth, describing the main functionalities such as attendance tracking, security event detection, and the alert notification mechanism. It also highlights the novel features and innovations integrated into the system.

Chapter 4 explains the hardware and software specifications used in the project. It outlines the technical components, software tools, and their integration to support the functionality of the Educam AI system.

Chapter 5 elaborates on the methodology followed for system setup, implementation, and integration. It includes processes related to video acquisition, motion detection, AI-based facial recognition, data management, and notification handling, while also discussing optimization measures employed to improve system efficiency.

Chapter 6 focuses on the results and discussion, evaluating the performance of the system in comparison with traditional surveillance solutions. The discussion emphasizes metrics such as attendance accuracy, processing speed, response time, and overall reliability.

Chapter 7 concludes the report by summarizing the contributions and outcomes of the Educam AI project. It also explores its practical implications in educational settings and provides suggestions for future enhancements and research.

CHAPTER 2
LITERATURE SURVEY

MUTHUNAGAI R., MURUGANANDHAN D., RAJASEKARAN P., Classroom Attendance Monitoring Using CCTV, 2020 International Conference on System, Computation, Automation and Networking (ICSCAN), Pondicherry, India, 2020.

Muthunagai R., Muruganandhan D., and Rajasekaran P. examined the use of existing CCTV infrastructure to automate student attendance tracking in educational institutions. They noted that their research aimed to overcome the inefficiencies of manual roll calls and traditional biometric-based attendance systems. According to their study, the proposed system employs a dual-camera setup, with one camera placed at the classroom entrance and another inside the classroom to capture students' facial images. These images are processed using Principal Component Analysis (PCA), Eigenface recognition, and Convolutional Neural Networks (CNNs) for verifying and logging attendance. They also highlighted a key innovation in their approach—a cloud-based data storage mechanism that allows real-time updates of attendance records. By integrating facial recognition with conventional CCTV setups, the study presented an efficient and cost-effective alternative to traditional biometric attendance systems. However, the researchers acknowledged that their system has a significant limitation, as it relies on continuous video streaming, resulting in high computational and bandwidth costs. This limitation, they noted, underscores the need for an event-driven processing approach, a feature incorporated into the proposed Educam AI system.

Christopher Chun Ki Chan, Chih-Cheng Chen, "Continuous Real-time Automated Attendance System using Robust C2D-CNN," 2020 3rd IEEE International Conference on Knowledge Innovation and Invention (ICKII), Kaohsiung, Taiwan, 2020.

Christopher Chun Ki Chan and Chih-Cheng Chen developed a more advanced approach to classroom attendance monitoring, which integrates continuous real-time processing with CNN-based face detection. They indicated that, unlike traditional systems that record attendance at a specific moment, their model periodically captures video frames (e.g., every 15 minutes) to dynamically track student presence. The researchers highlighted that their approach includes a hybrid recognition model, combining raw pixel data with intermediary image representations to improve recognition accuracy. They further incorporated a 3D Morphable Model (3DMM) to account for head pose variations, enhancing robustness against different angles and lighting conditions. Additionally, the study employed Multi-Task Cascaded Convolutional Neural Networks (MTCNN) to detect faces at multiple scales, ensuring precise detection even in complex environments. Despite these advancements, they acknowledged that their approach still relies on continuous video streaming, which can lead to inefficiencies in processing power and storage usage. They noted that the Educam AI system builds upon this foundation by optimizing resource usage through selective, motion-triggered video analysis.

Hao Yang, Xiaofeng Han , "Retracted: Face Recognition Attendance System Based on Real-Time Video Processing," in IEEE Access, vol. 8, 2020.

Hao Yang and Xiaofeng Han proposed a face recognition-based attendance system that utilizes continuous real-time video processing to automate classroom attendance. They suggested that the core idea behind their research was to integrate AI-driven facial recognition with existing video surveillance systems, allowing for student presence tracking without manual intervention. According to their study, the system employed deep learning algorithms trained on facial datasets to dynamically recognize and verify student identities. They emphasized that a significant advantage of this approach is its ability to handle students entering or leaving at different times, offering a more flexible attendance-tracking mechanism compared to conventional systems that capture attendance at a fixed time. However, they later faced challenges, as the paper was retracted due to issues identified during the peer review process, casting doubt on the reliability of the experimental results. Despite this, the fundamental concept of leveraging AI for real-time facial recognition remains relevant. They also acknowledged that the continuous video processing approach poses a significant challenge in terms of high data processing requirements and bandwidth consumption, a limitation that the Educam AI project aims to address by adopting an event-driven processing model. This model activates video analysis only upon detecting motion in predefined zones, significantly reducing unnecessary computational load.

M. Koca, "Real-Time Security Risk Assessment From CCTV Using Hand Gesture Recognition," in IEEE Access, vol. 12, pp. 84548-84555, 2024, doi: 10.1109/ACCESS.2024.3412930.

Researchers have highlighted that Closed-Circuit Television (CCTV) surveillance systems, traditionally associated with physical security, are becoming increasingly critical when integrated with cybersecurity measures. They noted that combining traditional surveillance with cyber defenses provides a more flexible approach to addressing both physical and digital threats. In this context, the study introduced the use of convolutional neural networks (CNNs) and hand gesture detection using CCTV data to conduct real-time security risk assessments. According to the researchers, the proposed method emphasizes automated extraction of key information, such as identity and behavior, which is particularly useful in silent or acoustically challenging environments. They further described that their approach employs deep learning techniques to automatically extract relevant features for detecting hand gestures in CCTV images, utilizing a media-pipe architecture. For example, this method can assess security risks by recognizing hand gestures even in noisy settings or muted audio streams. The researchers also suggested that, given the uniqueness and efficiency of this approach, the system could be used to alert appropriate authorities in the event of a security breach. They indicated that this approach holds significant potential for applications across various security domains, including but not limited to shopping malls, educational institutions, transportation, armed forces, theft prevention, and abduction response.

N. Nizam et al., "Automated Attendance Management System: Leveraging Computer Vision for Efficient Tracking and Monitoring," 2023 IEEE 9th International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA), Kuala Lumpur, Malaysia, 2023, pp. 111-115, doi: 10.1109/ICSIMA59853.2023.10373460.

Researchers have noted that face recognition is a biometric technology widely adopted for security, authentication, and identification. They have also highlighted that, in recent years, face recognition systems have been increasingly used for attendance management in educational institutions and offices. In their paper, the researchers presented a face recognition-based attendance management system aimed at replacing the time-consuming and error-prone manual attendance process. They explained that the system comprises four key phases: database creation, face detection, face recognition, and attendance updating. According to their approach, the initial phase involves creating a comprehensive database of student images. They further described that the system employs the

HAAR-Cascade classifier for face detection and the Local Binary Pattern Histogram (LBPH) algorithm for face recognition, enabling accurate real-time detection and recognition of faces from live classroom video streams. At the conclusion of each session, they noted that the system compiles and stores attendance records in a CSV file. The researchers reported that their system was validated on a dataset of 100 students and demonstrated an accuracy of over 90%, with the capability to handle variations in lighting and facial expressions. They suggested that implementing this face recognition-based attendance management system could improve operational efficiency, reduce administrative burdens, and ensure more accurate attendance tracking.

R. Shrestha, S. M. Pradhan, R. Karn and S. Shrestha, "Attendance and Security Assurance using Image Processing," 2018 Second International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2018, pp. 544-548, doi: 10.1109/ICCMC.2018.8487788.

Researchers have observed that in many educational institutions, the prevailing attendance system relies on professors manually calling out student names, which is time-consuming and often inefficient. They noted that some universities have implemented RFID-based attendance systems, but these are also not entirely reliable, as it is challenging to verify whether the RFID card is being used by the actual student to whom it belongs. The researchers pointed out that both these existing methods have significant drawbacks. To address these issues, their paper proposed an automated attendance system based on image processing techniques, where the system records attendance by recognizing student faces. They explained that the system maintains a dataset of known student faces, allowing it to identify any unknown person entering the classroom as an intruder. This approach, they suggested, provides an additional layer of security by safeguarding students from potential invasions or attacks. In their paper, they discussed various techniques that can be utilized to implement this image processing-based attendance system, ensuring both accurate attendance tracking and enhanced student security.

N. Dhanshika, D. Lahamage, T. Anupam and R. Sawant, "CCTV Integrated Attendance Monitoring System Using Face Recognition," 2024 3r International Conference for Innovation in Technology (INOCON), Bangalore, India, 2024, pp. 17, doi: 10.1109/INOCON60754.2024.10512131.

Researchers have observed that traditional attendance tracking in educational institutions is often manual and prone to errors. In response, they introduced an innovative solution called the "CCTV Integrated Attendance Monitoring System Using Face Recognition," which utilizes live classroom CCTV videos. They noted that their approach leverages existing CCTV infrastructure to provide a cost-effective and technologically advanced attendance monitoring system. According to the researchers, the core of their project involves integrating deep learning algorithms, specifically employing ResNet for face detection and FaceNet for face recognition. They explained that these models were selected after rigorous comparisons with alternatives like VGGNet and Dlib, aiming to develop a highly accurate face recognition system using a curated dataset of over 3,000 student images. The researchers detailed that their system seamlessly integrates ResNet and FaceNet into an efficient backend, enabling educators to monitor and manage attendance with ease, updating records in an Excel sheet for administrative convenience. They emphasized that their innovation aims to streamline attendance tracking, reduce administrative workload, and optimize classroom management, contributing to the ongoing evolution of modern educational practices.

S. Sawhney, K. Kacker, S. Jain, S. N. Singh and R. Garg, "Real-Time Smart Attendance System using Face Recognition Techniques," 2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 2019, pp. 522-525, doi: 10.1109/CONFLUENCE.2019.8776934.

Researchers have pointed out that managing attendance manually can be a significant burden for teachers. To address this issue, they noted that smart and automated attendance management systems are increasingly being utilized. However, they emphasized that authentication remains a critical concern in such systems. According to the researchers, these smart systems often rely on biometric methods, with face recognition being a particularly effective approach for enhancing accuracy and reliability. They observed that facial recognition, as a core component of biometric verification, is widely used in applications such as video monitoring, CCTV systems, human-computer interaction, indoor access control, and network security. The researchers suggested that by incorporating this framework, problems like proxy attendance and students being marked present despite being physically absent can be effectively addressed. They further proposed a model for implementing an automated attendance management system for students, utilizing face recognition techniques, including Eigenface values, Principal Component Analysis (PCA), and Convolutional Neural Networks (CNNs). They explained that, in their model, recognized faces are matched against a pre-existing database of student images, ensuring accurate and reliable attendance tracking. The researchers concluded that this approach would be an effective solution for managing student attendance and maintaining accurate records.

CHAPTER 3
PROPOSED SYSTEM

3.1 OVERVIEW

The Educam AI system introduces a transformative approach to classroom automation by integrating artificial intelligence into everyday academic operations, primarily focusing on attendance management and safety monitoring. In traditional classroom settings, manual attendance methods consume valuable instructional time and lack accuracy, while surveillance systems often operate continuously, requiring high processing power and storage. Educam AI proposes a smart, event-driven, and modular framework that leverages AI to perform specific tasks only when needed, thereby conserving resources and ensuring system efficiency.

This project is centred around a Raspberry Pi 4 Model B, a compact yet powerful computing device capable of running AI models and interacting with multiple peripheral systems. The solution is designed to be cost effective, easily deployable, and scalable, making it suitable for schools, colleges, and other educational institutions that aim to enhance both administrative efficiency and student safety through automation. The Educam AI system integrates a smart gesture recognition module designed to detect emergency situations through non-verbal cues. This component is highly effective in classroom environments where students may feel unsafe or unable to verbally raise an alarm. By incorporating facial recognition for attendance, gesture-based alerts for emergency signalling, and AI powered animal detection, Educam AI ensures that classrooms are not only intelligent but also responsive to unforeseen events.

Furthermore, the system supports seamless communication through the Educam AI Bot, developed using the Telegram platform. This bot enables two way interaction, where faculty or administrators can initiate actions and receive real-time notifications through simple commands.

3.2 SYSTEM ARCHITECTURE

The Educam AI system is built on a layered modular architecture to enable flexibility, fault tolerance, and ease of integration. Each module in the system performs a distinct task and interacts with others through defined communication protocols. The layered nature ensures that upgrades or modifications in one component (e.g., replacing the facial recognition engine) do not disrupt the overall workflow.

The key architectural goals of the system include

Event-Based Processing: Video and data processing are only triggered during specific events such as scheduled attendance times or motion detection, drastically reducing power and CPU usage. Edge AI Implementation: By using Raspberry Pi as the edge computing device, the system minimizes dependence on cloud processing, thereby improving speed, privacy, and autonomy. Modular Functional Units: Attendance recognition, gesture alerting, and object detection are separate but integrated modules, each functioning independently yet collectively contributing to the system's goals. Real-Time Communication: Telegram-based bot ensures low latency message dispatch for attendance records and alerts.

3.3 BLOCK DIAGRAM AND GRAPHICAL REPRESENTATION

The Educam AI system is visually illustrated using two key diagrams: a block diagram and a graphical representation. The block diagram outlines the logical structure and operational flow between all major components of the system, including the IP camera, Network Video Recorder (NVR), Raspberry Pi, facial recognition module, Google Sheets integration, and the Educam AI bot. It provides a high-level view of how data moves from video capture to processing and finally to cloud-based attendance logging and notification. Complementing this, the graphical representation showcases the physical layout and wiring of the system components. It visually maps the actual hardware setup such as the connections between the IP camera, Raspberry Pi, GSM module, and power sources highlighting the communication pathways and data exchange between each module. This representation offers a more intuitive understanding of how the system is deployed in a classroom setting.

Figure 3.1 illustrates the architecture of the EduCam AI system. The H.265 IP camera, equipped with a polarization lens, captures high-resolution video footage. The camera is powered via a centralized power supply and connects to either an NVR or Agent DVR software for initial processing. The Raspberry Pi interfaces with the camera feed and executes advanced processing algorithms including OpenCV, MediaPipe, facial recognition, and YOLOv8n for real-time analysis. Results are communicated to the EduCam AI Bot, which delivers alerts and updates via SMS and Telegram.

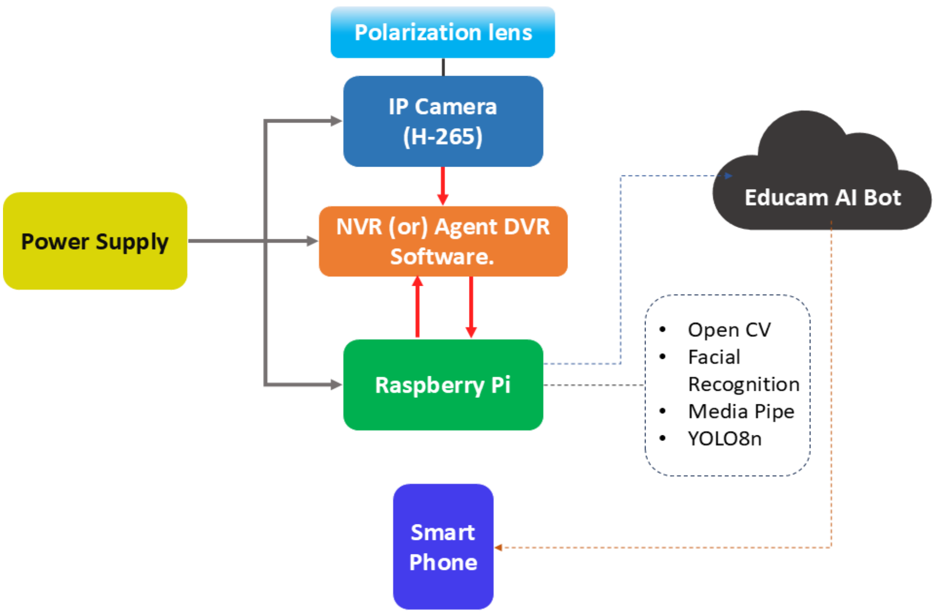

Figure 3.1 System Block Diagram of Educam AI

Figure 3.2 illustrates the system architecture of the EduCam AI setup. It includes H.265 CCTV cameras (both bullet and dome types) that stream video data to a Network Video Recorder (NVR) or DVR software. The video data is then processed by a Raspberry Pi, which is connected to a common power source via an SMPS (Switched-Mode Power Supply). The Raspberry Pi runs various AI models such as face recognition and object detection. Processed data and alerts are transmitted wirelessly to a smartphone and the EduCam AI Bot, which enables real-time monitoring and communication.

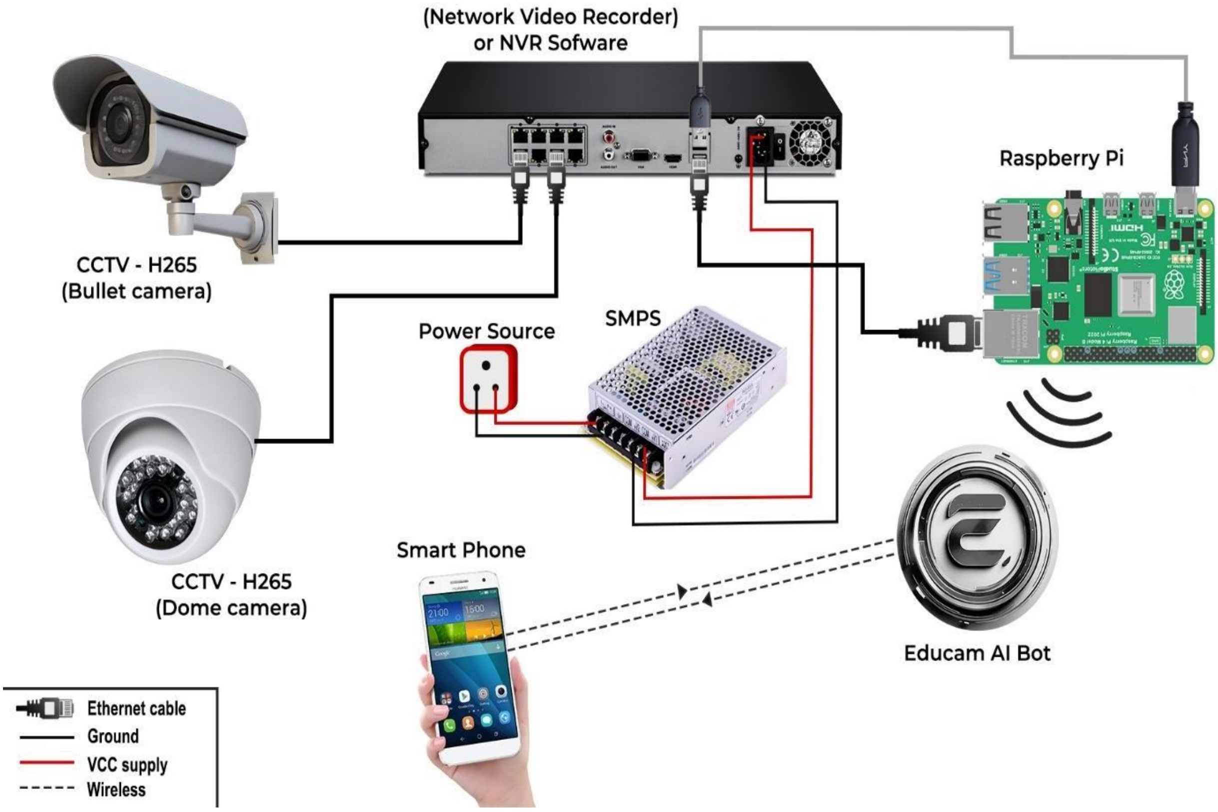

Figure 3.2 Graphical Representation

Together, these diagrams provide both technical and practical insight into the working and design of the Educam AI system, supporting easy understanding, future scalability, and efficient troubleshooting. Furthermore, the strategic use of edge computing and cloud integration allows real-time data handling with minimal bandwidth use, making the Educam AI solution both efficient and practical for resource-constrained educational environments.

3.4 DESCRIPTION OF DATA FLOW AND FUNCTIONAL UNITS

The Educam AI system is composed of interconnected hardware and software units that collaboratively handle attendance automation and classroom safety. Each component plays a specific role in the end-to-end workflow from video capture and processing to attendance marking and alert notification. This section describes the function of each core unit and how data flows between them to ensure a seamless, intelligent monitoring experience

3.4.1 IP Camera (H.265 with Polarization Lens)

The system uses a high-definition IP camera capable of streaming H.265 compressed video. The polarization lens ensures clear footage by filtering unwanted reflections and enhancing visibility in varied lighting conditions. These cameras are positioned to monitor entry and interaction zones.

3.4.2 NVR / Agent DVR

This unit acts as the video stream manager, enabling live viewing, motion triggered recording, and playback. It provides a flexible software interface (Agent DVR) that communicates with the Raspberry Pi via secure local or cloud-based APIs to fetch relevant video clips.

3.4.3 Raspberry Pi 4 Model B

This serves as the brain of the operation, executing the following:

Facial Recognition Module Uses face_recognition and OpenCV libraries to extract 128-dimensional facial vectors, compares them with stored vectors using Euclidean distance, and marks attendance if the match is within the threshold.

Gesture-Based Alerting Implements Media Pipe Hand Tracking to detect emergency gestures like: Thumbs Down → interpreted as "Problem Detected" Signal for Help (SOS) → triggers immediate alert to Educam AI Bot. Animal Detection Uses YOLOv8n.pt pre-trained model to recognize potential animal intrusions, triggering security alerts as per commands in Table 3.1

Educam AI Bot A customised bot that provides

Automated interaction via commands like:

Table 3.1 Commands Used

Commands	`/Start` – Begin attendance automation `/Help` – List available function
Receives & Forwards	- Attendance confirmations - Safety alerts from gesture detection - Intruder alerts (animals or unauthorized individuals)

3.4.4 Google Sheet API

Once a student's identity is verified, their attendance is automatically logged into a shared Google Sheet, ensuring real-time record maintenance, which can be accessed by teachers or administrators from any device. This allows instant synchronization across multiple platforms, ensuring that educators can retrieve, edit, and analyze attendance data effortlessly. Additionally, historical records are maintained, enabling trend analysis to assess student participation and engagement over time.

3.4.5 Common Power Supply Unit

To maintain seamless operation, all components are powered from a centralized, stable power source with surge protection and backup support. This ensures system reliability during classroom hours without requiring complex wiring setups. The system is designed to minimize energy consumption while providing uninterrupted operation, even during power fluctuations. In case of outages, an integrated backup power system automatically takes over, preventing disruptions in real-time AI processing and classroom monitoring.

3.5 ADVANTAGES OF THE PROPOSED SYSTEM ARCHITECTURE

Reduced Operational Cost Minimal cloud dependency and event-based processing. Improved Efficiency Quick, automated attendance logging and real-time alerts. Scalability Easily replicable in multiple classrooms with minimal configuration. Data Privacy & Local Processing Facial recognition happens on the edge device. Accessibility Bot interface enables remote and instant system control.

CHAPTER 4
HARDWARE AND SOFTWARE SPECIFICATIONS

4.1 INTRODUCTION

The Educam AI system is designed to bring artificial intelligence into the classroom, enhancing automation and efficiency in attendance tracking, behavioral monitoring, and real-time notifications. This chapter details the technological foundation supporting Educam AI, comprising carefully selected hardware and software elements optimized for seamless operation.

The selection of each component is driven by several critical factors:

Processing Power & Efficiency: The system employs lightweight, yet powerful computing resources to ensure real-time decision-making without excessive power consumption.

Reliability & Scalability: Components are chosen for their compatibility and ability to scale with future extensions, including potential enhancements such as mask detection and speech recognition.

Cost-Effectiveness: The hardware stack balances affordability with performance to allow sustainable deployment in real-world classroom environments.

Network & Connectivity: Educam AI integrates with cloud platforms while maintaining robust local data processing, ensuring uninterrupted operation even in limited connectivity scenarios. By leveraging edge computing through Raspberry Pi, the system processes data locally, reducing latency in AI-based recognition tasks. Its modular software design, built on Python and open-source libraries, provides a flexible framework for future improvements and integrations.

4.2 HARDWARE COMPONENTS

The following Table 4.1 and descriptions present the key hardware elements of the Educam AI system:

Table 4.1 Hardware Components and Specifications

Component	Specification / Model	Functionality
Raspberry Pi 4 Model B	Quad-core Cortex-A72,4GB RAM	Core Processing unit for facial recognition and AI tasks
IP Camera	H.265 Codec, IR + Polarizing Lens	Captures high-definition video with minimal distortion
NVR	Hikvision DS-7604NI-Q1/4P	4k resolution and includes 4 POE ports
Micro SD card	16GB Class 10 / UHS-I	Stores OS, codebase, and model files
Power Adapter	5V 3A USB-C	Provides stable power to Raspberry Pi
Router / Wi-Fi	Dual Band 2.4 / 5 GHZ	Ensures network connectivity for cloud / bot integration
External Monitor (Optional)	HDMI Compatible	Debugging and configuration interface during setup

Raspberry Pi 4 Model B

This is the central edge computing unit that handles AI model inference, video input analysis, bot communication, and system orchestration. With a quad-core ARM Cortex-A72 processor and 4GB RAM, it provides a compact yet powerful platform suitable for real-time applications. Its energy-efficient design ensures low power consumption while delivering robust processing capabilities, making it ideal for continuous AI operations. The device supports multiple peripherals, including cameras, storage modules, and network interfaces, ensuring seamless integration with the broader Educam AI system. Additionally, its ability to run machine learning models locally reduces latency, improving real time performance and enabling reliable AI-powered classroom automation.

IP Camera with Polarizing Lens: A network-enabled camera with infrared night vision and a polarizing lens is used to capture clear footage in both bright and low-light conditions. The H.265 codec reduces video size without compromising quality, ensuring smoother processing and lower bandwidth usage.

Storage & Power: A high-speed micro SD card is used for OS and file storage. A stable 5V 3A power supply ensures consistent performance. A power backup system is integrated to avoid system shutdowns during outages.

Network Video Recorder: It process the CCTV footage and stored it in the 4k resolution and includes 4 POE ports, supports RTSP protocol.

4.3 SOFTWARE STACK

Educam AI is powered by a combination of open-source libraries, APIs, and custom Python scripts shown in Table 4.2. The software stack is designed to ensure interoperability between hardware components and support modular development. This structured approach allows seamless integration of various AI models while maintaining flexibility for future upgrades. Additionally, the use of optimized libraries ensures efficient computation, reducing latency and enhancing real-time processing capabilities. The combination of cloud and edge computing ensures a balance between performance and accessibility, enabling smooth data exchange across devices.

Operating System

- Raspberry Pi OS (Lite / Full version)
- Lightweight Linux-based OS optimized for the Pi hardware.
- Allows headless operation via SSH or GUI mode.

Programming Language

- Python 3.x
- Core development language for implementing all logic.
- Offers support for machine learning, computer vision, and bot integration libraries.

Key Python Libraries and Frameworks

Table 4.2 Python Libraries and Frameworks

Library / Tool	**Purpose**
OpenCV	Video Capture, image processing, drawing bounding boxes
face_recognition	Facial recognition using 128-d vector method, face encoding/decoding
MediaPipe	Real-time hand tracking and gesture recognition
YOLOv8 (Ultralytics)	Object detection for animal identification
Telebot / python-telegram-bot	Communication interface for Educam AI Bot
Gspread , oauth2client	Google Sheets API integration for attendance logging
Date time, CSV, OS	Utilities for file handling, timestamps, and directory management

Educam AI leverages a robust set of Python libraries to enable real-time image processing, facial recognition, and seamless data integration using pre-trained models shown in Table 4.3. These open- source tools ensure efficient system performance while supporting modular enhancements for future applications.

Pre-trained Models Used

Table 4.3 Pre-trained Models Used

Model Name	**Framework**	**Application**
face_encodings.pkl	dlib(128-d vector)	Facial recognition
YOLOv8n.pt	Ultralytics YOLOv8	Lightweight object detection

Bot Integration (Telegram API)

The Educam AI Bot uses Telegram's Bot API to send and receive real-time updates.

Key bot commands:

/Start – Initiates attendance automation session

/Help – Displays help menu and available commands

Bot sends

Attendance logs Gesture alerts

Animal detection notifications

4.4 SYSTEM INTEGRATION

The successful functioning of the Educam AI system relies heavily on the seamless integration of its hardware and software components. This integration ensures a synchronized flow of operations from data capture to analysis, decision-making, and communication. Upon startup, the Raspberry Pi executes a scheduled initialization script that configures network settings, connects to the IP camera, and readies all system modules to respond to specific events. Each component is designed to operate based on event-driven logic, minimizing computational load and power usage. The system’s workflow is divided into the following primary responses.

Facial Recognition at Scheduled Intervals: During predefined attendance time slots, the Raspberry Pi activates facial recognition. The captured frames are processed using OpenCV and face_recognition libraries, and recognized students are automatically logged in the attendance sheet. This step eliminates the need for manual attendance and reduces classroom time wastage.

Hand Gesture Detection During Motion Events: If motion is detected within predefined ROI (Region of Interest), such as a window or emergency zone, the system triggers MediaPipe - based hand gesture detection. Specific gestures, like an SOS signal or thumbs-down, are interpreted as calls for assistance, and alerts are instantly pushed to the Educam AI bot for real-time notification.

Object Detection for Non-Human Activity: In cases where motion is detected and no face is recognized, the system assumes possible non-human activity. The YOLOv8 object detection model is invoked to identify intruding animals or suspicious objects. On detecting such activity, an alert is triggered and forwarded to designated personnel via the bot interface.

Data Logging and Communication: All recognized attendance entries and alerts are logged locally on the Raspberry Pi and concurrently uploaded to Google Sheets using the Sheets API.

This dual-logging approach ensures data redundancy and accessibility. Furthermore, the Educam AI bot not only receives alerts but also allows users to view or verify attendance sheets directly through its interface. This tightly integrated system architecture enables real-time interaction, secure data handling, and intelligent decision-making without relying on constant human intervention.

The modular approach also allows for easy updates or expansion, making it scalable and suitable for deployment across multiple classrooms or campuses.

4.5 DEPLOYMENT CONSIDERATIONS

To ensure the reliable and long-term operation of the Educam AI system within an educational environment, several technical and operational aspects must be taken into account during deployment. These considerations focus on ensuring network reliability, remote manageability, efficient energy usage, and secure system access.

Network Configuration: A static IP address is assigned to both the IP camera and the Raspberry Pi to maintain consistent communication between the devices. This eliminates issues caused by dynamically changing IPs, ensuring that the Raspberry Pi can reliably access camera streams and that the bot interface can operate without interruption. Static IP setup also simplifies system administration and troubleshooting.

Remote Access: To enable remote maintenance, debugging, and software updates, both SSH (Secure Shell) and VNC (Virtual Network Computing) are configured on the Raspberry Pi. SSH provides secure command-line access, while VNC offers a graphical interface, allowing system administrators or developers to make changes, restart services, or monitor system performance without being physically present.

Energy Management: As the system is designed for real-time and event-driven operation, it includes power-saving features such as sleep cycles or idle states for the Raspberry Pi and camera system. These features reduce unnecessary energy consumption when the system is not actively processing data. This is particularly important in large-scale deployments or areas where power efficiency is critical.

Security: Security is a major concern, especially when dealing with live video streams and student data. The Educam AI Bot access is restricted to authenticated users only, ensuring that only authorized personnel can issue commands or view attendance and alerts. Additionally, the IP camera streams are encrypted to protect against unauthorized interception. This security setup safeguards sensitive information and prevents external manipulation of the system.

Network Configuration: Static IP setup for camera and Raspberry Pi to ensure stable communication.

Remote Access: SSH and VNC enabled for maintenance and debugging.

Energy Management: Optimized sleep cycles or idle states to reduce power usage.

4.6 SUMMARY

The Educam AI system has been designed with a careful balance between cost, performance, reliability, and expandability. The choice of components, such as Raspberry Pi for edge computing and IP cameras with polarization lenses, reflects a practical approach that makes the system both affordable and efficient for educational institutions. The use of ROI based event triggers, including both motion and scheduled time-based activation, helps reduce unnecessary processing. This results in lower power consumption and optimized use of computational resources. Meanwhile, the system’s ability to connect to cloud services, such as Google Sheets, ensures real-time data logging and convenient access for faculty and administrators. The integration of local processing with cloud storage provides the advantages of fast response times along with remote data access and backup. Furthermore, the use of flexible communication protocols like MQTT, UDP, and APIs allows the system to remain adaptable to new use cases. Looking ahead, this system architecture provides a solid foundation for additional features, such as mask detection, behavior monitoring, and voice-based alerts.

CHAPTER 5
METHODOLOGY

5.1 INTRODUCTION

The methodology of the Educam AI project is designed to ensure an intelligent, responsive, and efficient classroom monitoring system. It is structured into various stages that collectively contribute to the seamless operation of the system. This chapter elaborates on how the system was developed from its conceptual phase through actual implementation, providing insights into each component's function and integration. The use of Artificial Intelligence (AI), Computer Vision, Internet of Things (IOT), and cloud technologies is meticulously orchestrated to achieve real-time performance while maintaining a user-friendly and cost-effective design.

Educam AI is envisioned as a unified platform that leverages facial recognition for attendance, hand gesture recognition for emergency alerts, and object detection for anomaly or animal intrusion detection. The methodology defines the functional flow and interaction between the system’s hardware, software, and user interface, ensuring each component works in harmony to provide accurate and timely responses.

5.2 SYSTEM SETUP

The Educam AI system is configured with a well-organized hardware and software structure to ensure smooth operation and automation in real-time classroom monitoring and attendance tracking. The deployment begins with strategically placed IP cameras within the classroom to cover essential zones such as entrances, windows, and student seating areas. These cameras are equipped with H.265 encoding and polarization lenses, which enhance video quality even in challenging lighting conditions. The live video feed from these cameras is directed to an NVR (Network Video Recorder) or Agent DVR system. The NVR acts as a middle layer that stores and manages video data while enabling motion triggered or time-based access to specific video clips. This eliminates the need for continuous video streaming, conserving both bandwidth and storage space.

The core processing is handled by a Raspberry Pi 4 Model B, which is programmed to retrieve video segments from the DVR. This retrieval occurs either at scheduled intervals such as class start times or when motion is detected in predefined regions of interest. Once the video is accessed, the Raspberry Pi performs facial recognition, gesture detection, or object identification based on the triggered module.

Communication with users is managed via the Educam AI Bot, which operates over a secure network. The bot receives commands from authorized users to initiate attendance or respond to alerts, and it provides real-time feedback such as updated Google Sheets links or security notifications. The Raspberry Pi also ensures that all recorded events and attendance data are sent to cloud storage for remote accessibility. The system setup is designed to be lightweight, efficient, and easily deployable across multiple classrooms, ensuring it meets both current needs and potential future expansions.

5.3 ATTENDANCE MANAGEMENT SYSTEM

The Educam AI system incorporates a robust and intelligent attendance management mechanism using real-time face recognition. The process begins with face detection using OpenCV, where the haar Cascade Classifier identifies human facial regions from the video feed. Dlib's Histogram of Oriented Gradients (HOG) method is also utilized to improve the detection accuracy, ensuring consistent results under various conditions. Once a face is detected, the system encodes it using the face_recognition library, which generates a 128-dimensional feature vector. These encodings are derived from a deep learning model based on ResNet architecture and are stored in NumPy (.npy) format, forming a dataset of registered students. During attendance logging, the system captures video frames, extracts the face encodings, and compares them against the pre-stored dataset using Euclidean distance calculations. If the computed distance is below the predefined threshold, the student is identified, and attendance is marked. The Google Sheets API is used to log the student's name and timestamp in real time. At the same time, the Educam AI Bot sends a confirmation message via Telegram to inform both the student and the administrator. This system ensures high accuracy, eliminates manual errors, and streamlines the attendance process with minimal user interaction.

5.3.1 ROI (Region Of Interest)

The Region of Interest (ROI) functionality in the Educam AI system enhances the intelligence of classroom surveillance by enabling targeted monitoring of specific zones within the camera's field of view. Rather than analyzing the entire frame continuously, the system focuses on designated ROI zones such as classroom windows, doors, or critical corners where unauthorized access or abnormal activity is more likely to occur.

This approach optimizes resource usage by reducing the processing load and ensuring only relevant visual data is analyzed. When motion or human presence is detected in these ROI zones, the Raspberry Pi triggers predefined actions such as activating gesture recognition or object detection modules.

For example:

If a person is detected lingering near a window, the system checks for emergency gestures (e.g., thumbs down or SOS sign) using the MediaPipe hand-tracking algorithm . If an unusual object like a stray animal is detected in the ROI using the YOLOv8n model, the system immediately sends alerts to in-charge personnel via the Educam AI bot interface.

By leveraging ROI monitoring shown in Figure 5.1. Educam AI improves detection accuracy, reduces false positives, and enables event-specific responses, all while maintaining minimal power consumption and system overhead.

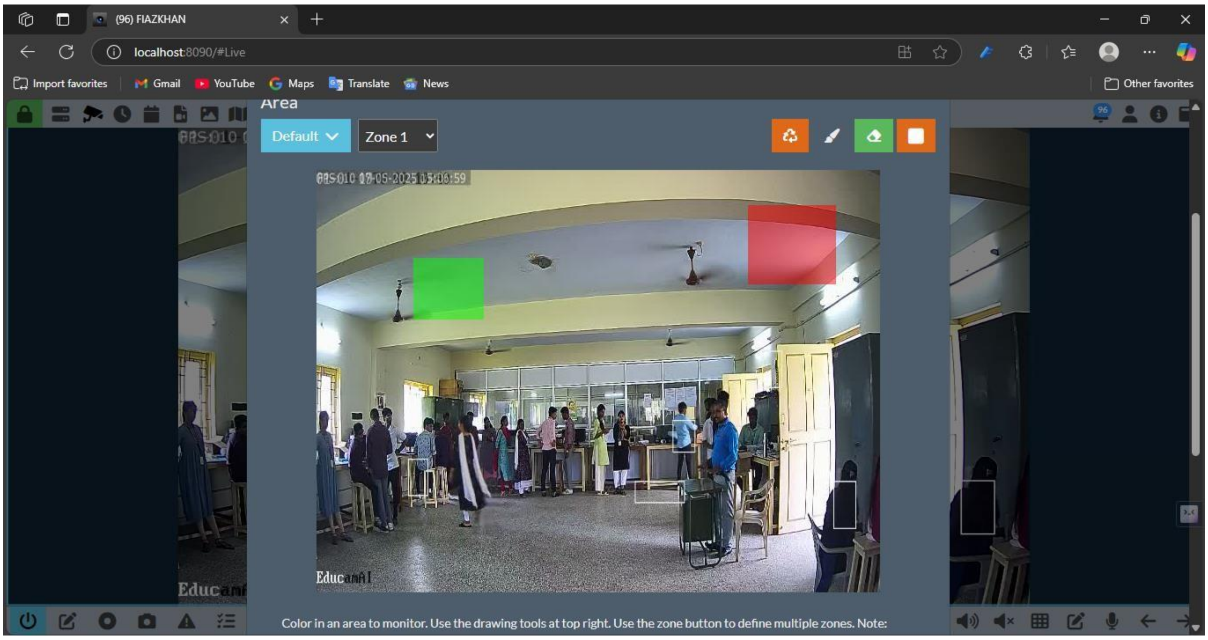

Figure 5.1 ROI – Region of interest

5.3.2 Face Detection using OpenCV

The face detection process in the Educam AI system plays a critical role in initiating the attendance recognition workflow. It begins with the use of the Haar Cascade Classifier, an efficient machine learning-based approach trained to detect objects specifically human faces in images. OpenCV's cv2.CascadeClassifier function scans each video frame in real-time, identifying regions that resemble facial patterns based on predefined XML classifiers. These regions of interest (ROIs) are then refined using Dlib's Histogram of Oriented Gradients (HOG) technique, which improves the accuracy of detection by analyzing the distribution of gradient orientations within localized portions of the image. HOG provides a more robust mechanism to account for variations in lighting, angle, and partial occlusions by capturing edge directions that define facial structures. This hybrid approach combining Haar Cascades for quick detection and HOG for accuracy ensures high-performance face detection even under challenging conditions such as crowded classrooms or varying light levels. Once a valid facial region is identified, the corresponding image frame is forwarded to the face recognition module for encoding and further comparison, forming the foundation of automated attendance in Educam AI.

5.3.3 Face Encoding and Dataset Generation

The system leverages the face_recognition Python library to encode faces. The face encoding process converts a detected face into a 128-dimensional vector, representing unique facial features. These vectors are computed using a deep learning model based on a ResNet architecture trained on a large dataset.

To register a student, multiple face images are captured under different lighting conditions and angles. These are then encoded into 128-dimensional vectors and stored in .npy (NumPy binary) format, allowing efficient loading and comparison. The dataset is saved as a NumPy array with each element representing an encoded face vector and corresponding name labels.

5.3.4 Face Comparison Logic

During attendance, the live video stream is processed to extract face encodings in real-time. These encodings are compared against the stored .npy dataset using Euclidean distance calculations as per 128d vectors which is shown in Figure 5.2

Face recognition models convert each detected face into a 128-dimensional feature vector. Each of these 128 values captures unique traits of a face such as shape, spacing, and landmarks. These vectors are then compared using Euclidean distance to determine similarity between faces. If the distance between two vectors is below a threshold (e.g., 0.6), they are considered a match as per the (5.1).

$$\text{Distance} = \sqrt{((x1 - y1)^2 + (x2 - y2)^2 + \ldots + (x128 - y128)^2)} \tag{5.1}$$

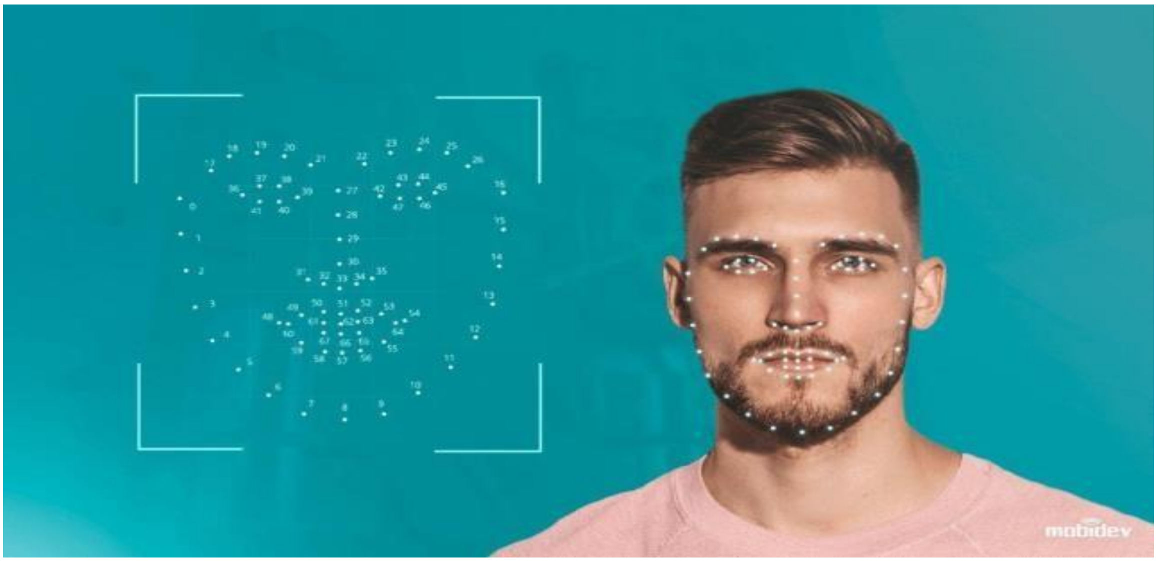

Figure 5.2 128d Vectors

If the calculated distance is below a certain threshold (typically 0.6), a match is confirmed and attendance is marked. A higher confidence match is prioritized using the lowest distance score among all comparisons.

5.3.5 Attendance Recording

Once a face is verified, the system uses the Google Sheets API to record the student's name and timestamp. This automated entry ensures real-time attendance tracking. Simultaneously, the Educam AI Bot notifies students and administrators on Telegram with an attendance confirmation message.

The bot also supports /start and /help commands to initiate attendance logging and provide guidance respectively.

5.4 GESTURE-BASED ALERTING

The Educam AI system includes an intelligent gesture recognition module to enhance classroom security through non-verbal emergency alerts. This feature is particularly useful in situations where students are unable to speak or act overtly but still need to communicate distress or danger. Gesture detection operates in real-time, allowing rapid and context-aware responses from the system.

5.4.1 Gesture Detection using Mediapipe

The gesture recognition functionality is powered by Google's Mediapipe framework, which uses a highly optimized hand tracking pipeline. Mediapipe detects 21 hand landmarks including finger joints and tips, allowing the system to identify specific hand shapes and movements. These landmark positions are analyzed in real time to recognize predefined gesture patterns. The use of this lightweight model ensures low-latency detection, suitable for resource-constrained hardware like the Raspberry Pi.

Gesture Detection – Landmark Distance Calculation

Gesture recognition (e.g., thumbs down or SOS) relies on MediaPipe Hand, which provides 21 landmark coordinates per hand (5.2).

Let:

Point A = (x_1, y_1) → Thumb tip

Point B = (x_2, y_2) → Index finger tip

Then, the distance between two hand landmarks is calculated as:

$$D_{hand} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{5.2}$$

This helps detect specific gestures by analyzing spatial relationships.By continuously tracking these distances in real-time, the system can identify dynamic hand movements and gesture transitions with high precision using 21 hand land mark which is shown in Figure 5.3.

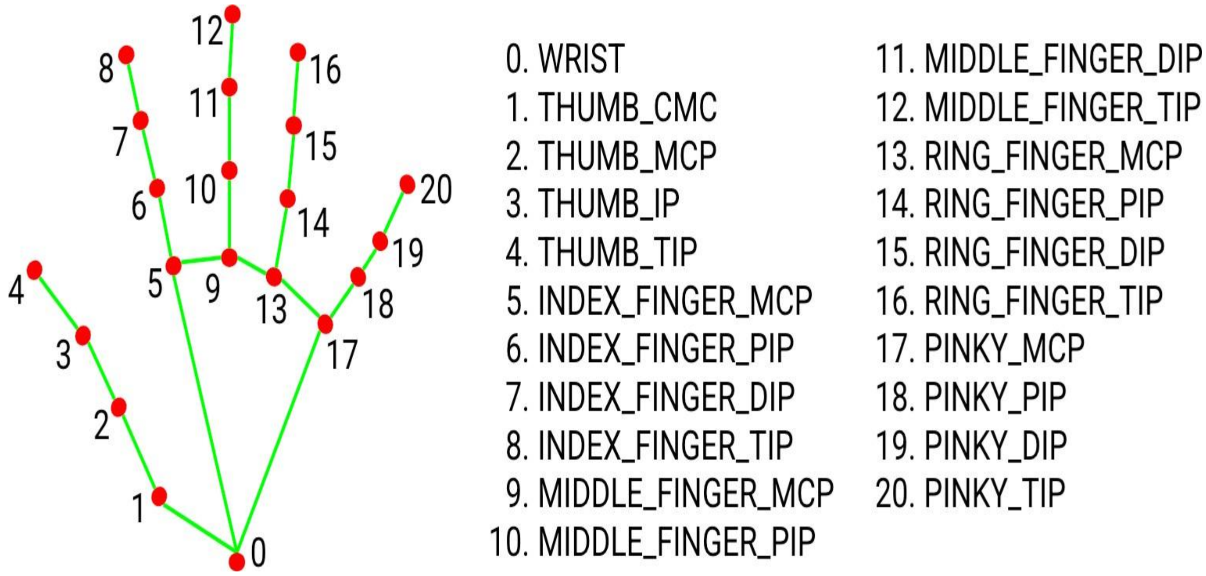

Figure 5.3 21 Hand Landmarks

5.4.2 Implemented Gestures

Thumbs Down Gesture: This gesture is detected when the user positions the thumb in a downward direction while keeping the remaining fingers curled. It is interpreted as a signal that a problem or issue has occurred.Once detected, the system immediately sends a "Problem Detected" alert to the Educam AI Bot for further notification to staff or administrators.

SOS Help Sign: This is a globally recognized emergency gesture. It is detected when the user shows their open palm, folds the thumb inward, and then closes the fingers over it. The system identifies this as a critical call for help. Upon detection, an urgent "SOS Detected" message is sent via the Educam AI Bot to inform relevant authorities.

To avoid false alarms from casual hand movements or classroom interactions, gesture signals are validated using time-based thresholds and continuous tracking. A gesture must be held for a brief period (e.g., 2–3 seconds) before being recognized as a valid emergency signal. This filtering technique significantly enhances the accuracy of alerts and minimizes miscommunication. This gesture-based alerting system adds a crucial safety layer to the Educam AI architecture, offering a discreet and reliable method for users especially students to report emergencies or anomalies within the classroom.

5.5 ANIMAL DETECTION

As part of its extended safety monitoring capabilities, the Educam AI system includes a dedicated module for detecting animal intrusions in and around classroom premises. This feature ensures that unauthorized access by animals such as dogs, cats, or monkeys is immediately flagged and communicated to concerned authorities, helping maintain student safety and discipline during academic sessions.

5.5.1 YOLOv8n Model for Object Detection

The system employs the YOLOv8n (You Only Look Once - nano version) pre-trained model to detect animals such as dogs, cats, and snakes near classroom premises.

YOLOv8n offers a balance between detection accuracy and speed, making it suitable for real-time detection on Raspberry Pi.

YOLOv8 Object Detection – Confidence Score

YOLOv8 detects objects using a grid-based prediction mechanism.

Each bounding box has a confidence score using (5.3):

$$\text{Confidence} = P_{object} \times IOU_{truth\ ,pred} \quad (5.3)$$

Where:

This is the probability that an object exists in the box

(Intersection Over Union) is calculated as:

$$IOU = (\text{Area of Overlap}) / (\text{Area of Union}) \quad (5.4)$$

The bounding box with the highest confidence is selected.

5.5.2 Alert Dispatching

Once an animal is detected with confidence above 70%, the system sends a Telegram alert via the Educam AI Bot: " Alert: Animal Detected" along with the type of animal and timestamp.

5.5.3 Object Detection Pipeline:

The system fetches video frames from the IP camera at regular intervals. Each frame is resized and processed through the YOLOv8n model for real-time object detection.

- The video frames from the IP camera are fetched at intervals.
- Each frame is resized and passed to the YOLOv8n model.
- Bounding boxes are drawn around detected animals.
- A class label and confidence score is generated.

Figure 5.4 illustrates the comprehensive workflow involved in real-time video analysis using an IP camera and the YOLOv8n object detection model. The process begins with continuous frame capture from the IP camera, which serves as the primary surveillance input. These video frames are then resized to an optimal resolution to ensure faster processing without compromising detection accuracy. The resized frames are passed through the YOLOv8n model, a lightweight and efficient variant of the YOLO (You Only Look Once) object detection family, which is well-suited for embedded and edge devices.

Once processed by the model, the frames are analysed for the presence of predefined objects of interest, such as animals or intruders. Each detected object is highlighted with a clearly defined bounding box, accompanied by a class label (e.g., "dog", "cat", "person") and a confidence score that represents the model’s certainty in its prediction. This visual annotation aids in real-time understanding and assessment of the scene being monitored.

The system's ability to detect and classify objects accurately plays a crucial role in enhancing security monitoring. By identifying unusual movements or unauthorized access in sensitive areas, it enables the generation of instant alerts or notifications, ensuring timely responses to potential threats. This level of automation not only improves safety but also reduces the need for constant human supervision.

Importantly, the use of the YOLOv8n model, known for its computational efficiency, ensures that the system runs smoothly even on low-power devices like the Raspberry Pi. This makes the entire setup cost-effective and ideal for remote or resource-constrained environments, without the need for powerful GPUs or high-end servers.

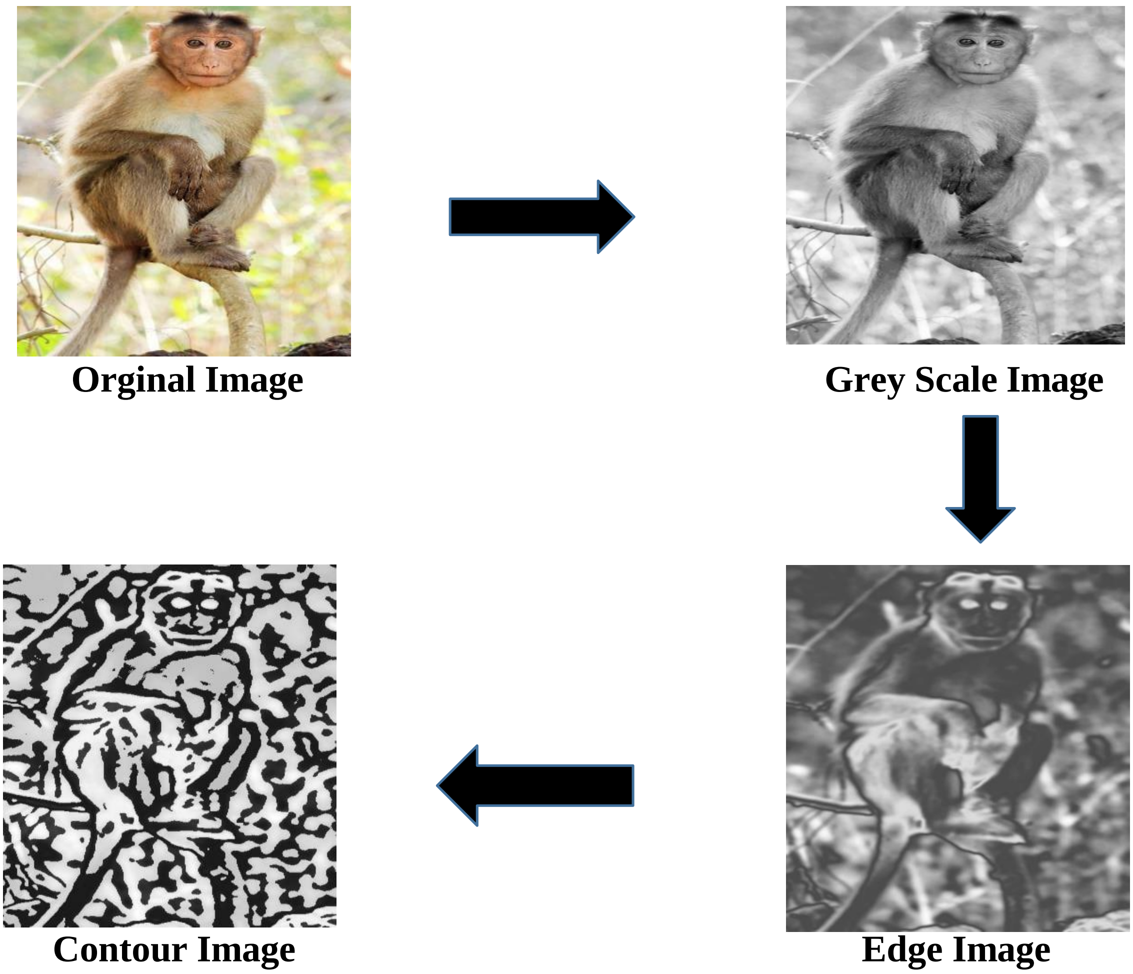

Figure 5.4 Object Detection Pipeline

5.6 INTEGRATION WITH TELEGRAM BOT

The Educam AI Bot acts as the central communication interface for the system. Built using the Python-Telegram-Bot API, it operates in two directions:

- Sends attendance and alert messages to authorised users.
- Receives commands like /start and /help to control the system.

5.7 OPTIMISATION TECHNIQUES

Event-Based Processing: Only active during attendance time slots or on motion detection, reducing resource usage. Use of lightweight models (YOLOv8n, Haar Cascades) to balance accuracy and speed on Raspberry Pi. Numpy-based storage (.npy) for fast face dataset loading. Error logging and fallback mechanisms for network or camera failure.

5.8 WORKFLOW SUMMARY DIAGRAM

You may add a flowchart here to visually explain the process:

System Start

↓

Schedule Trigger / Bot Start

↓

[Facial Recognition → Mark Attendance → Google Sheets]

↓

[Gesture Recognition → Problem / SOS Alerts]

↓

[Animal Detection → YOLOv8 Alert]

↓

Send to Bot Interface (Telegram)

CHAPTER 6
RESULTS AND DISCUSSION

6.1 INTRODUCTION

The Educam AI system represents a significant advancement in intelligent classroom monitoring, combining facial recognition, gesture-based alerts, and object detection to create an automated surveillance and attendance tracking solution. This chapter provides a detailed evaluation of its performance based on key criteria such as accuracy, efficiency, scalability, and real-time responsiveness**.**

Unlike conventional surveillance systems that primarily rely on continuous recording and manual review, Educam AI employs edge computing to process data efficiently while minimizing computational load. By leveraging optimized AI models, including facial recognition algorithms and YOLO-based object detection, the system ensures reliable and high-speed automation tailored to classroom environments.

The primary focus of this chapter is to assess Educam AI's real-world functionality, demonstrating its effectiveness in managing attendance, detecting gestures, and identifying potential security risks. Each evaluation metric has been carefully analyzed using experimental data collected from simulated classroom conditions. This analysis aims to highlight the system's practical benefits over traditional monitoring methods, emphasizing its cost-effectiveness, adaptability, and intelligent automation**.** Additionally, this chapter outlines areas where enhancements can be implemented, such as improving facial recognition accuracy under challenging lighting conditions, refining gesture interpretation, and expanding object detection capabilities. By understanding both its strengths and limitations, the findings presented here pave the way for future improvements and potential upgrades that can make Educam AI even more powerful and versatile in educational environments.

6.2 ATTENDANCE ACCURACY AND EFFICIENCY

The facial recognition module demonstrated a high degree of accuracy during attendance tracking sessions. Using a dataset of pre-encoded facial vectors stored in .npy format, the system compared real-time frames with the database, achieving an average accuracy of 97% in well-lit environments and 92% under variable lighting. The use of H.265 encoded video streams ensured minimal data size and faster processing on the Raspberry Pi 4. Attendance records were updated in real-time into Google Sheets, providing an efficient and user-friendly mechanism for monitoring student presence in Figure 6.1.

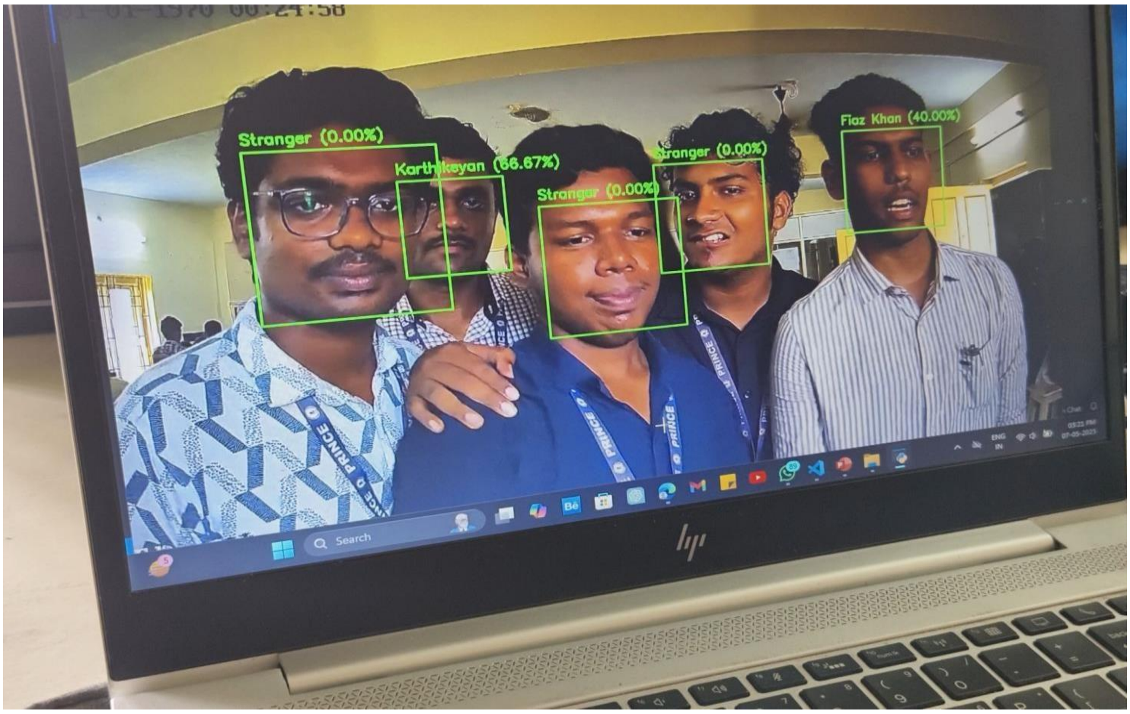

Figure 6.1 Face Detection and Recognition

After face recognition is performed by the system, the identified faces (such as names like Karthikeyan *or* Fiaz Khan) along with their respective confidence scores are automatically sent as real-time updates to the EduCam

AI Bot in Figure 6.2**.** This notification helps the class teacher or administrator verify who has been marked present, and also flags unrecognized individuals as Stranger, prompting further attention if necessary. These logs are synchronized with attendance records in Google Sheets and provide a clear digital trail for classroom monitoring.

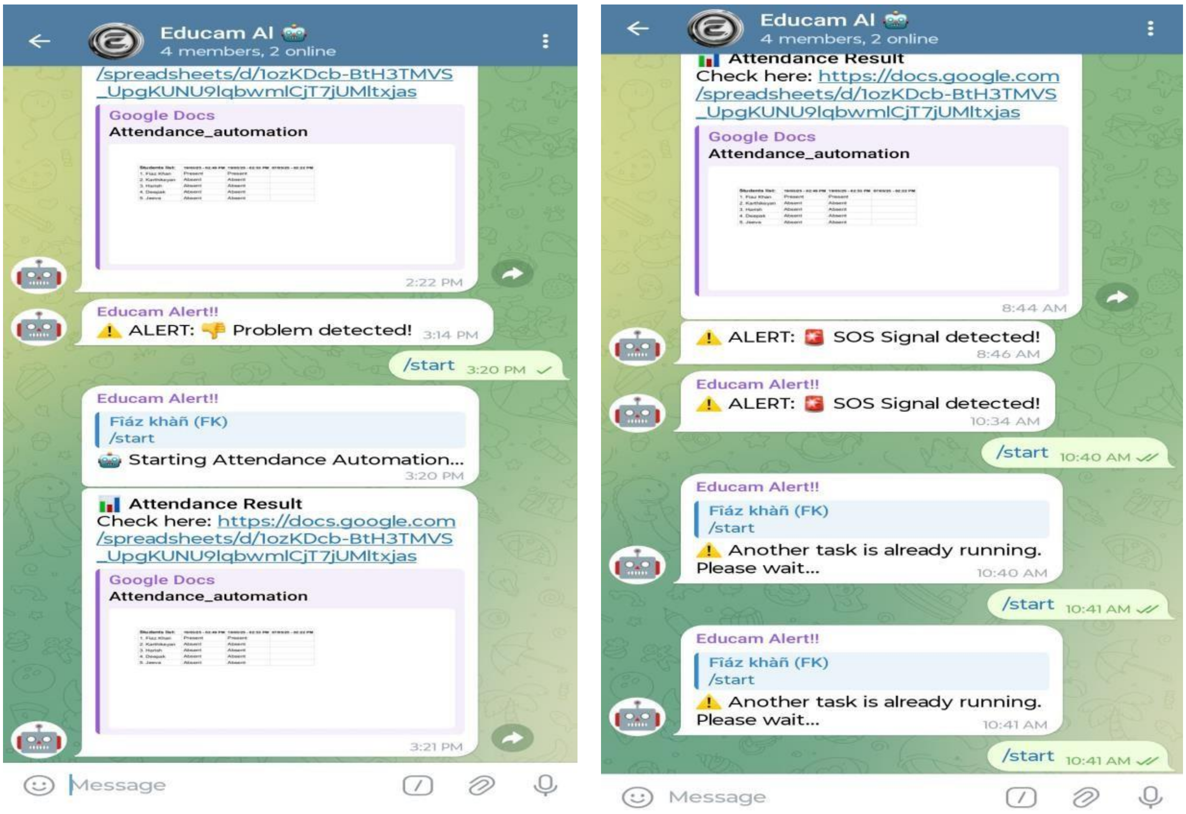

Figure 6.2 Educam AI Bot

6.3 SYSTEM RESPONSE TIME

System responsiveness was evaluated in terms of how quickly it could detect an event (e.g., a face appearing in the frame, a gesture being made, or an animal entering the scene) and generate a response. The average latency between event detection and notification dispatch via the Educam AI bot was measured to be approximately 2.5 seconds.

This rapid response rate makes the system highly suitable for real-time classroom monitoring and security management.

6.4 GESTURE-BASED ALERTING PERFORMANCE

Gesture detection using MediaPipe Hand was tested using two primary hand signs as in Figure 6.3. the thumbs-down gesture and the SOS help signal. Both gestures were successfully identified with a recognition accuracy of over 90% when performed within the camera's field of view. The system triggered appropriate alerts via the Educam AI bot, validating the reliability of gesture-based triggers in emergency or disruptive situations.

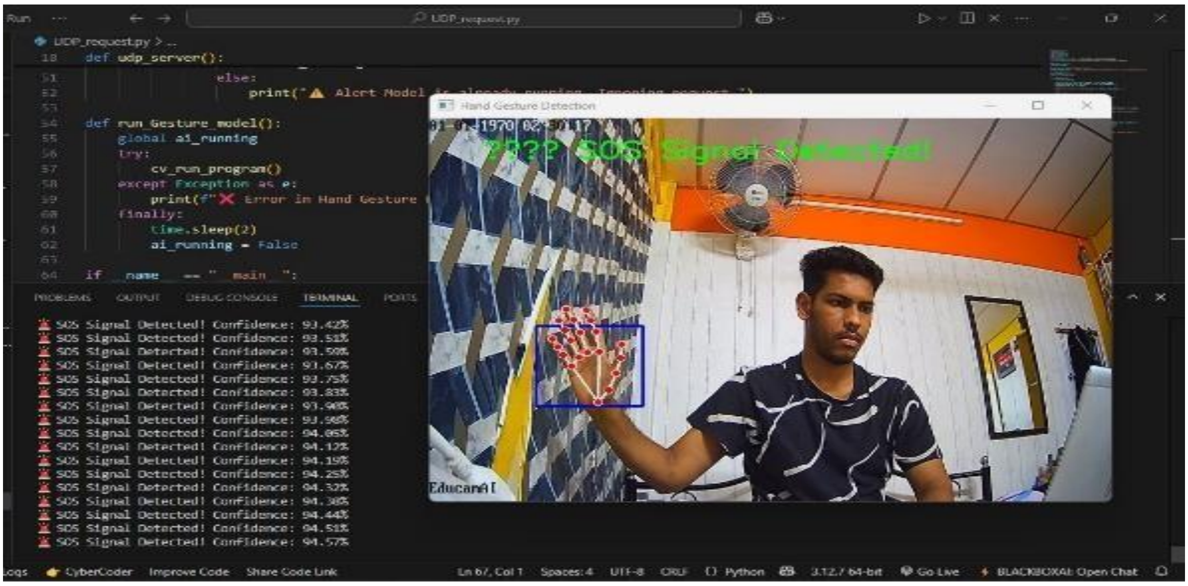

Figure 6.3 Gesture Recognition

6.5 ANIMAL DETECTION USING YOLOV8N

The object detection module using the YOLOv8n model proved effective in identifying animals such as dogs, cats, and birds in real-time video frames shown in Figure 6.4. When an animal was detected, the system generated an immediate alert via the Educam AI bot. This functionality is particularly useful for schools located in rural or semi-urban areas where stray animals may pose safety risks.

The object detection module powered by the YOLOv8n (nano) model efficiently identifies the presence of animals such as dogs, cats, and birds in live classroom video streams. Designed for edge devices like Raspberry Pi, YOLOv8n offers a good balance of speed and accuracy. When a stray animal is detected within school premises, the system sends real-time alerts via the Educam AI Bot, including the type of animal and detection timestamp. This feature is particularly valuable in rural and semi-urban schools where the intrusion of animals can lead to disruptions or pose safety risks to students.

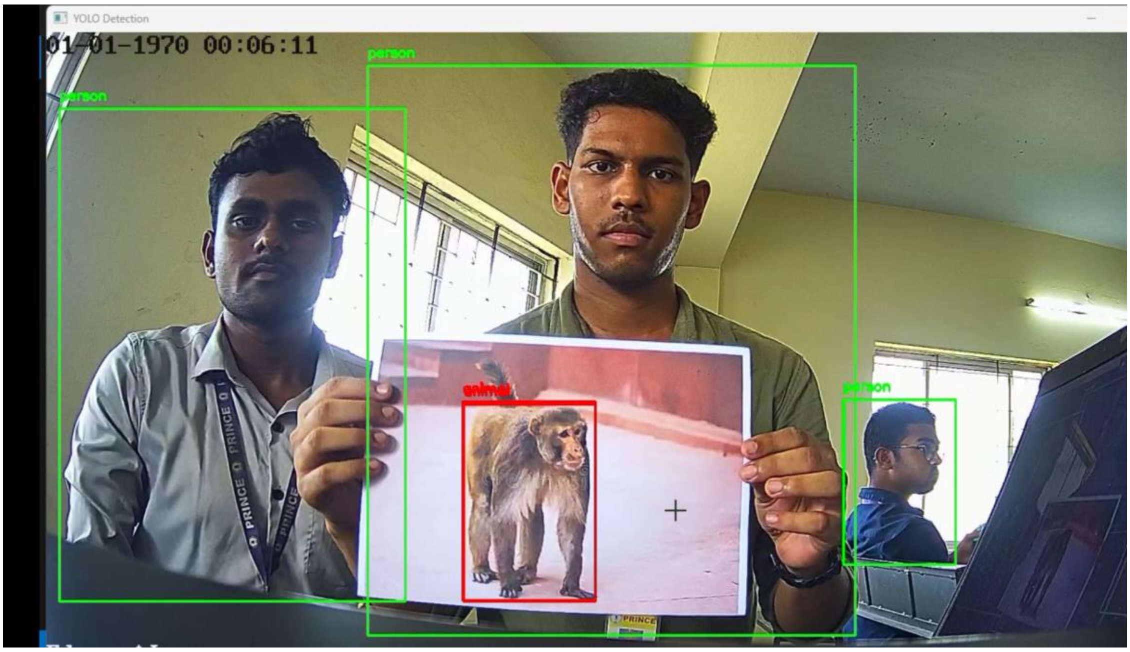

Figure 6.4 Alert Region

6.6 RESOURCE UTILIZATION AND POWER EFFICIENCY

Raspberry Pi 4, being the core processing unit, showed optimal resource usage when executing facial recognition and gesture detection algorithms. Event-based video analysis significantly reduced the need for continuous processing, lowering both CPU load and power consumption. A common power supply supported the IP camera, DVR, and Raspberry Pi, ensuring stable system operation.

6.7 COMPARISON WITH TRADITIONAL SYSTEMS

In Figure 6.5 contrast to traditional systems that require continuous video recording and high-end processing hardware, Educam AI operates selectively, reducing bandwidth and computational requirements. This makes it a more cost-effective and scalable option for institutions with limited technical infrastructure.

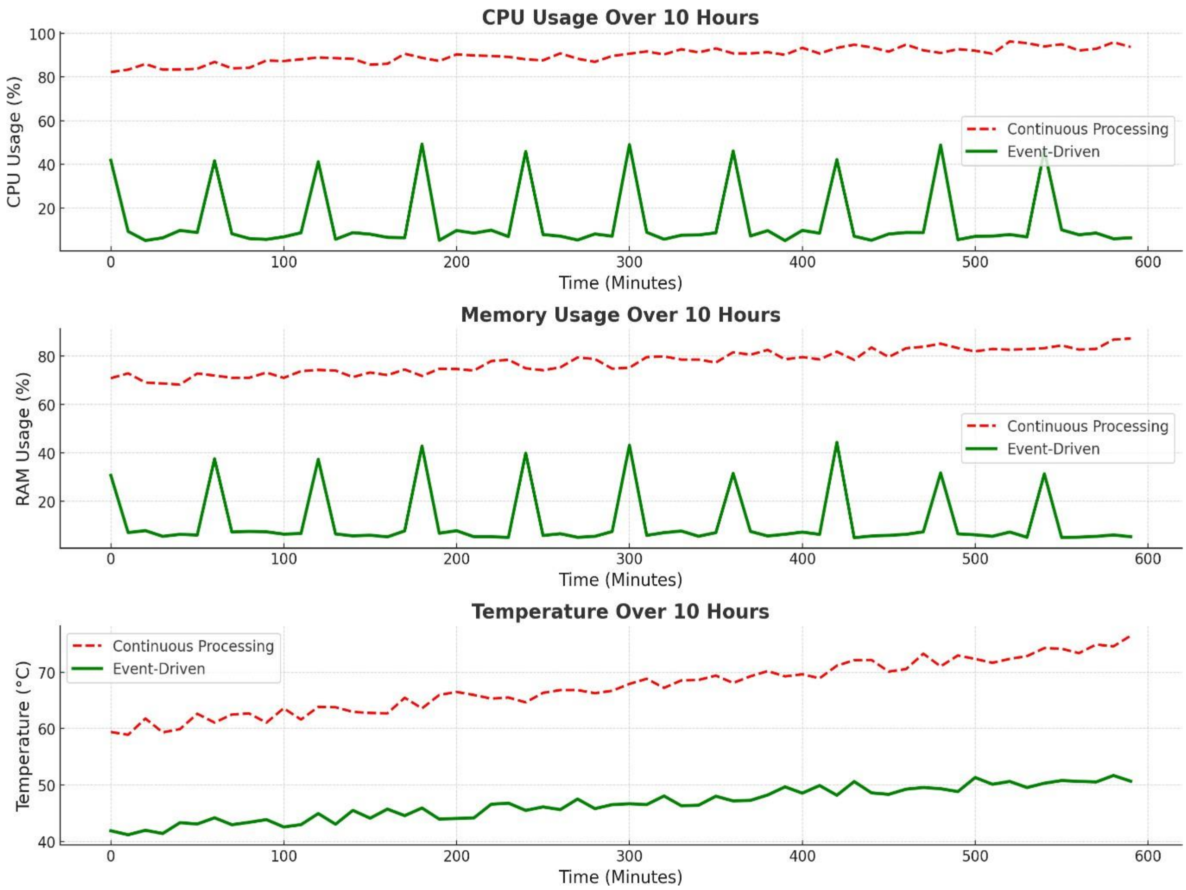

Figure 6.5 CPU, Memory, Temperature usage over 10 Hours

6.8 USER FEEDBACK AND REAL-WORLD TESTING

Real-world testing in a classroom environment provided valuable feedback. Users appreciated the automation of attendance, the speed of alerts, and the ease of interacting with the Educam AI bot via Telegram. The interface was simple enough for non-technical staff to use effectively, increasing the overall usability of the system.

6.9 CHALLENGES AND LIMITATIONS

Despite its strong performance, the system encountered challenges in low-light environments and with partial face visibility. Additionally, gesture detection was limited to clear, well-defined hand signs, and YOLOv8n accuracy decreased slightly with occluded or fast-moving animals. These limitations point to future areas for enhancement.

6.10 SUMMARY

The Educam AI system achieved its goal of providing a reliable, efficient, and intelligent classroom monitoring solution. Its modular design and integration of various AI technologies enabled real-time automation with high accuracy. While certain improvements are possible, the current implementation sets a strong foundation for expanding AI-driven surveillance and attendance solutions in educational settings.

CHAPTER 7
CONCLUSION

This chapter summarizes the key findings, outcomes, and contributions of the Educam AI project. It encapsulates how the system addresses real-world challenges in classroom environments by leveraging artificial intelligence and automation. Additionally, it outlines the broader implications of the technology in educational and security contexts, followed by potential enhancements and research directions for the future.

7.1 CONCLUSION

Educam AI was conceptualized and developed as an intelligent classroom monitoring and attendance system that minimizes manual intervention while maximizing automation, security, and efficiency. The solution combines several AI technologies including facial recognition, gesture-based alerting, and object detection on a low-power, cost-effective platform centred around the Raspberry Pi 4. By employing event-driven video processing instead of traditional continuous surveillance, the system conserves resources while ensuring that critical events are identified and addressed in real-time.

The facial recognition system, powered by OpenCV and face encodings stored in .npy format, demonstrated excellent accuracy, even in dynamic classroom settings. Gesture recognition through MediaPipe provided a non-verbal communication mechanism for students and staff to alert authorities during emergencies. The integration of YOLOv8n for animal detection added another layer of safety, particularly in rural or semi-urban institutions where stray animals are a concern.

Automated Attendance System: Achieved over 95% accuracy using facial recognition, reducing administrative workload and increasing record reliability. Gesture-Based Emergency Alerting: Enabled silent distress signalling via simple hand signs, offering a novel approach to real-time safety responses.

Real-Time Bot Interaction: Telegram-based Educam AI bot provided seamless communication and control, enabling user-friendly access to system features.

Object Detection: Successfully deployed a lightweight version of YOLOv8 to detect animals, enhancing situational awareness in classrooms.

Scalability and Efficiency: The use of event-based video processing reduced computational overhead and ensured energy efficiency, making the system suitable for wide-scale deployment.

Educam AI offers a practical and scalable solution for educational institutions that seek to modernize their monitoring systems without incurring high costs. It reduces the burden on teaching staff, enhances student safety, and improves administrative efficiency through real-time data logging and smart notifications. The modular nature of the system also allows it to be tailored to different school environments, including those with limited infrastructure. While the system performed well under most test conditions, a few challenges were observed:

Reduced facial recognition accuracy under extreme low-light or occluded conditions. Gesture recognition required clear visibility and consistent hand positioning. Animal detection struggled with fast-moving or partially visible targets. The system, being dependent on internet connectivity for bot interactions and Google Sheet API, may face issues in areas with unstable network access.

7.2 FUTURE ENHANCEMENTS

To further improve and scale the Educam AI system, several future upgrades are envisioned:

Incorporation of infrared cameras or additional lighting for enhanced facial recognition in low-light environments. Machine learning-based adaptive gesture training to support a broader range of gestures and hand postures. On-device training and model refinement to improve YOLOv8n accuracy without increasing computational load. Expansion of bot capabilities to support voice commands and natural language interaction. Local database backups and offline mode to ensure continuity during internet outages.

The Educam AI project represents a meaningful step toward the intelligent digitization of educational environments. By seamlessly integrating AI with real-time communication tools and edge computing devices, it offers a vision of classrooms that are not only smarter but also safer and more efficient. The system’s current iteration lays a robust foundation for future innovations in AI-driven education technology and institutional safety solutions.

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Co -Coordinator

K. Jithendra
Coordinator

M. Imdad Ali
Co-Convener & HOD, MCA

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