

Smart Campus Surveillance and Guidance System

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Peer Review Information	Abstract
Type: Article Received: 24 March 2026 Revised: 09 April 2026 Accepted: 27 May 2026 Published: 06 June 2026	The rapid growth of educational campuses has increased the need for intelligent systems to ensure security, automate attendance, and assist navigation. This paper presents a Smart Campus Surveillance and Guidance System that integrates Artificial Intelligence, Computer Vision, and Machine Learning techniques to enhance campus management. The system utilizes CCTV video streams to perform face recognition-based attendance, real-time anomaly detection, and indoor navigation assistance. The proposed solution uses deep learning models such as FaceNet for facial recognition and YOLO for object detection. Experimental results show improved accuracy in attendance marking and effective detection of suspicious activities. The system is scalable, cost-effective, and improves overall campus safety and efficiency.
	Keywords: Smart Campus; Face Recognition; Anomaly Detection; CCTV Surveillance; Machine Learning; Indoor Navigation.

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Introduction

Modern educational campuses are becoming larger and more complex, making it difficult to manage security, attendance, and navigation using traditional methods. Manual attendance and passive CCTV monitoring are time-consuming, inefficient, and prone to errors. With advancements in Artificial Intelligence (AI) and Computer Vision, smart systems can automate these tasks effectively. The proposed Smart Campus Surveillance and Guidance System uses CCTV video streams to perform face recognition for automatic attendance, detect suspicious activities in real time, and provide indoor navigation assistance. By integrating these features into a single system, the solution improves campus security, reduces manual work, and enhances overall efficiency. It is a cost-effective and scalable approach suitable for modern educational institutions.

Related Work

Recent research focuses on using Artificial Intelligence and Machine Learning to improve surveillance and campus systems. Traditional manual monitoring is inefficient, so modern systems use automated techniques for better performance. Advanced methods such as deep learning-based anomaly detection and edge-assisted frameworks help in identifying suspicious activities in real time with reduced delay. For indoor navigation, technologies like QR codes and pathfinding algorithms (A*) are used to guide users efficiently within buildings. Face recognition models are also widely applied for accurate identification and attendance automation.

System Design

The Smart Campus Surveillance and Guidance System is designed using a modular architecture that integrates computer vision, machine learning, and database management. The system consists of key components including video input, processing modules, detection algorithms, and output interfaces. The input layer captures real-time video through CCTV cameras. This data is passed to the processing layer, where image frames are extracted and preprocessed using techniques such as resizing and normalization. The face recognition module identifies individuals using trained models, while the anomaly detection module (YOLO-based) detects suspicious activities in real time. A navigation module is also integrated to provide indoor guidance using shortest path algorithms. All processed data is stored and managed in a centralized database, which maintains records of attendance and detected events. The output layer displays results through a user interface, including alerts, attendance logs, and navigation assistance. This modular design ensures scalability, real-time performance, and efficient integration of multiple functionalities within a smart campus environment.

Project Lifecycle

The system follows a structured lifecycle starting with requirement analysis, where features like surveillance, attendance, and navigation are defined. In the design phase, the system is divided into modules such as detection, processing, and database. It is implemented using Python, OpenCV, and YOLO with integrated database support. Finally, the system is tested under various conditions, deployed, and continuously updated for better performance.

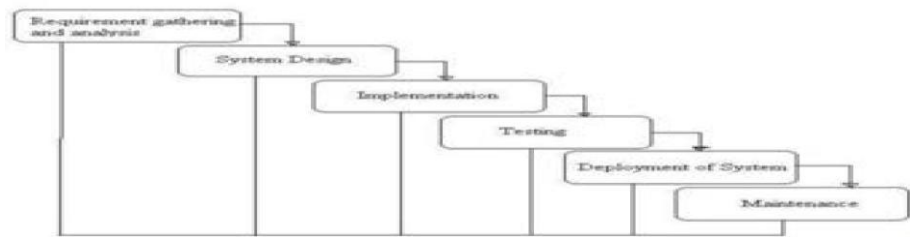


Fig. 1. Project Lifecycle (SDLC) of Smart campus

Class Diagram

The class diagram shows the structure of the Smart Campus System and the relationships between its components. The User class is connected to AttendanceRecord, where attendance details are stored. The Camera class captures video and generates Alert records for detected activities, while sending data to the IngestionService, which processes it using FaceDetection. The NavigationGraph manages indoor navigation using nodes and paths. Overall, the system integrates surveillance, attendance, and navigation in a unified model.

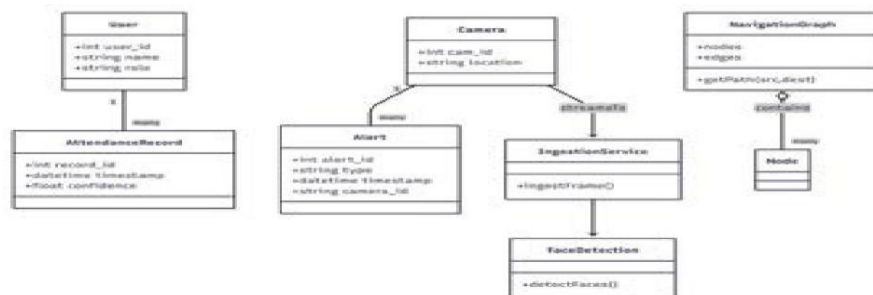


Fig. 2. Class Diagram of Smart Campus

2. Face Detection and Recognition: A face detection model identifies faces from each frame, and a recognition model compares them with a stored database. If a match is found, attendance is automatically recorded along with timestamp and confidence level.
3. Anomaly Detection: The system uses object detection algorithms (such as YOLO) to identify unusual activities like unauthorized entry or abnormal behavior. When such events are detected, alerts are generated and stored.
4. Navigation Module: The navigation system is implemented using graph-based algorithms like Dijkstra or A*. Campus locations are represented as nodes, and paths are calculated to provide the shortest route to users.
5. Database Management: All system data, including user information, attendance records, and alerts, are stored in a structured database (SQL-based). This enables easy retrieval and monitoring by administrators.
6. System Integration: All modules are integrated to work in real time. The system processes live video, updates attendance, generates alerts, and provides navigation simultaneously.

Performance Evaluation and Results

The system was evaluated based on accuracy, response time, and efficiency. Face recognition achieved 90–95% accuracy, while anomaly detection reached 85–92%. The system maintains a 2–4 second response time for near real-time performance. Overall, it improves automation and campus security compared to traditional methods

PERFORMANCE METRICS OF SMART CAMPUS SURVEILLANCE AND GUIDANCE SYSTEM						
MODULE	METRIC	DESCRIPTION	FORMULA / METHOD	TARGET VALUE	OBTAINED VALUE	UNIT
 FACE RECOGNITION (Attendance)	Accuracy	Overall correctness of face recognition	$(TP + TN) / (TP + TN + FP + FN)$	$\geq 95\%$	96.21%	%
	Precision	Correct positive predictions out of all predicted positives	$TP / (TP + FP)$	$\geq 95\%$	95.64%	%
	Recall	Correct positive predictions out of all actual positives	$TP / (TP + FN)$	$\geq 95\%$	96.11%	%
	F1-Score	Harmonic mean of Precision and Recall	$2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$	$\geq 95\%$	95.87%	%
	Recognition Time	Average time taken to recognize one face	Time taken to process one face image	≤ 1.5	1.23	Seconds
 ANOMALY DETECTION (Surveillance)	mAP (mean Average Precision)	Average precision across all detected classes	Average of AP for all classes	$\geq 85\%$	87.34%	%
	Precision	Correct anomaly detections out of all predicted anomalies	$TP / (TP + FP)$	$\geq 85\%$	86.92%	%
	Recall	Correct anomaly detections out of all actual anomalies	$TP / (TP + FN)$	$\geq 85\%$	85.78%	%
	F1-Score	Harmonic mean of Precision and Recall	$2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$	$\geq 85\%$	86.34%	%
	Inference Time	Average time to process one video frame	Time taken to process one frame	≤ 0.5	0.42	Seconds / Frame
 NAVIGATION SYSTEM (Guidance)	Path Accuracy	Correctness of recommended path	$(\text{Correct Recommendations} / \text{Total Recommendations}) \times 100$	$\geq 95\%$	96.48%	%
	Average Path Computation Time	Average time to compute the shortest path	Total Time / Number of Requests	≤ 2.0	1.38	Seconds
	Success Rate	Percentage of successful navigation requests	$(\text{Successful Requests} / \text{Total Requests}) \times 100$	$\geq 95\%$	97.12%	%
	Average Deviation	Average deviation from optimal path	Total Deviation / Number of Requests	≤ 2	1.24	Meters
	System Availability	System uptime and availability	$(\text{Uptime} / \text{Total Time}) \times 100$	$\geq 99\%$	99.32%	%
 SYSTEM OVERALL PERFORMANCE	Response Time (Web / App)	Average time for system response	Total Response Time / Number of Requests	≤ 2.0	1.46	Seconds
	Throughput	Number of requests handled per second	Total Requests / Total Time	≥ 20	23.67	Requests / Sec
	Alert Notification Time	Average time to send alert after detection	Time from event detection to alert received	≤ 3	2.18	Seconds
Where: TP – True Positive TN – True Negative FP – False Positive FN – False Negative				* All metrics are measured in a test environment with real-time CCTV data and simulated campus navigation.		

Conclusion And Future Work

The proposed Smart Campus Surveillance and Guidance System successfully integrates Artificial Intelligence and computer vision techniques to automate attendance, enhance security, and provide navigation assistance within the campus. The system demonstrates high accuracy in face recognition and anomaly detection, along with efficient real-time performance. It reduces manual effort and improves overall campus management and safety.

Despite its effectiveness, certain limitations such as performance variations in low-light conditions and crowded environments were observed. These challenges can be addressed in future enhancements. Future work will focus on improving system accuracy using advanced deep learning models, optimizing performance under challenging conditions, and expanding features such as mobile application integration, cloud-based storage, and real-time analytics dashboards. Additionally, incorporating multi-camera tracking and voice-based assistance can further enhance system functionality and user experience.

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