Archives available at journals.mriindia.com

International Journal on Advanced Electrical and Computer Engineering

ISSN: 2349-9338

Volume 14 Issue 01, 2025

Assessment of Smart Campus Surveillance and Guidance Approaches

[1]Prof. Y.L.Tonape, [2]Sawant Eshwari, [3]Thombare Kiran, [4] Wayase Sejal

[1 2 3 4 5] S.B.Patil college of engineering, Indapur

Peer Review Information

Submission: 11 Sept 2025

Revision: 10 Oct 2025

Acceptance: 22 Oct 2025

Keywords

Smart Campus, Face Recognition, Anomaly Detection, Machine Learning, Indoor Navigation, CCTV Surveillance, Attendance Tracking, Graph-based Pathfinding, Activity Recognition, Campus Security.

Abstract

The increasing size and complexity of modern campuses has created challenges in ensuring safety, security, and seamless navigation for students and visitors. Traditional manual surveillance methods and static campus maps are inadequate in providing real-time monitoring and dynamic guidance. Human-dependent monitoring is error-prone and inefficient, while students and visitors often face difficulties in locating classrooms, administrative offices, or other facilities. Moreover, issues such as inconsistent attendance tracking, class bunking, and unidentified anomalies further highlight the limitations of current systems.

To address these challenges, this project proposes a software-only, machine learning–based Smart Campus Surveillance and Guidance System that leverages existing CCTV infrastructure. The system integrates face recognition for automated attendance tracking, anomaly detection for suspicious activities, and an indoor navigation module for real-time campus guidance. The solution operates without the need for additional IoT or blockchain devices, making it lightweight, cost-efficient, and scalable.

The architecture comprises multiple software modules including preprocessing, face recognition, activity detection, and navigation built on graph-based pathfinding algorithms. Backend APIs and a database store all student, attendance, and anomaly data, while a user-friendly frontend provides real-time alerts and navigation. By combining deep learning models such as YOLO, FaceNet, and LSTMs with pathfinding algorithms like Dijkstra and A*, the system ensures intelligent monitoring, early anomaly detection, and smooth user navigation.

This system has the potential to revolutionize campus security and student management by automating critical tasks, reducing manual errors, and improving campus safety standards. Beyond surveillance, it also enhances user experience by providing personalized route guidance and timely notifications. With privacy safeguards, scalability features, and modular deployment, this project lays a strong foundation for the adoption of AI-driven smart campuses in the future.

Introduction

The concept of smart campuses has gained increasing importance in recent years as educational institutions expand in size and complexity. With thousands of students and visitors moving through campuses daily, ensuring safety, efficient navigation, and accurate record-keeping has become a major challenge.

Manual surveillance methods are no longer sufficient in handling large-scale environments, as they demand significant manpower and remain prone to oversight. Similarly, paper-based or manual attendance systems fail to provide accurate insights and are easily manipulated.

Machine learning has emerged as a transformative tool in addressing these challenges. Through advancements in computer vision, deep learning, and intelligent pathfinding algorithms, it is now possible to develop software-driven solutions that automate key campus operations. By leveraging existing CCTV cameras and digital infrastructure, campuses can shift toward automated systems that not only monitor activities in real time but also provide actionable insights through anomaly detection.

Face recognition technology enables seamless identification of students and ensures attendance records are accurate and reliable. Meanwhile, activity recognition and anomaly detection models ensure that unusual behaviors—such as fights, loitering, or unauthorized entry—are quickly flagged for administrator attention. Furthermore, campus maps can be digitized and represented as graphs, where shortest-path algorithms offer efficient indoor navigation. This reduces the frustration of navigating large campuses and enhances visitor experience.

In addition to operational efficiency, such a system supports institutional goals of improving safety, accountability, and technological modernization. By consolidating multiple intelligent features into one integrated framework, the Smart Campus Surveillance and Guidance System provides a comprehensive solution that can be customized for different educational institutions.

Problem Statement

Campuses often lack automated and intelligent surveillance systems to monitor students and visitors. Manual monitoring is labor-intensive, prone to errors, and inefficient in real-time anomaly detection. Additionally, students and visitors struggle with navigating large and complex campuses, while attendance tracking remains inconsistent and often unreliable. These issues highlight the need for a machine learning–driven software system that integrates face recognition, anomaly detection, and navigation guidance to improve campus safety, efficiency, and user experience.

Literature Survey

1. FaceNet: A Unified Embedding for Face Recognition (Schroff et al., 2025)

FaceNet introduced a deep learning framework that directly learns a mapping from face images to a compact Euclidean embedding space. By using a triplet loss function, the model ensures that embeddings of the same person are clustered closely while embeddings of different people are pushed apart. This approach eliminated the need for handcrafted features, setting a new benchmark for face recognition accuracy. In the context of smart campuses, this method can provide reliable identity verification and automate attendance marking by comparing embeddings of live camera feeds with stored student data. The efficiency and robustness of FaceNet make it a suitable choice for deployment in real-time systems, even when dealing with diverse facial orientations and lighting conditions.

2. YOLO: Real-Time Object Detection (Redmon et al., 2025)

The YOLO (You Only Look Once) framework transformed the object detection domain by introducing a single-stage detector capable of real-time performance. Unlike previous multi-stage detectors such as Faster R-CNN, YOLO processes the entire image in one pass, dividing it into a grid and predicting bounding boxes and class probabilities simultaneously. This speed makes it highly effective for surveillance applications where real-time responses are critical. In a campus environment, YOLO can be employed for activity recognition, such as detecting students running, loitering, or engaging in unauthorized actions. Its ability to balance accuracy and speed is key in minimizing system latency while ensuring prompt alerts for anomalies.

3. RetinaFace: Single-stage Dense Face Localisation (Deng et al., 2025)

RetinaFace enhanced face detection by providing pixel-level localization, even in challenging conditions such as occlusion, low resolution, or extreme poses. By integrating joint extra-supervised and self-supervised multi-task learning, RetinaFace achieved high precision in face landmark localization. This is particularly important for surveillance systems where cameras capture faces under suboptimal conditions. On a smart campus, RetinaFace can improve attendance validation by ensuring accurate detection of students' faces in crowded hallways and classrooms. Its robustness across diverse visual environments reduces the risk of false negatives, thereby increasing the reliability of face-based monitoring systems.

4. Temporal Convolutional Networks for Action Recognition (Lea et al., 2024)

Temporal Convolutional Networks (TCNs) introduced a powerful framework for sequence modeling by applying convolutional operations over time-series data. Unlike traditional recurrent architectures such as LSTMs, TCNs exploit temporal dependencies more efficiently while maintaining parallelizability. In activity recognition, TCNs can identify prolonged or sequential behaviors such as walking, running, or loitering. For campus surveillance, this allows for the detection of suspicious behavior patterns before they escalate into incidents. The model's scalability and ability to process video streams make it a valuable addition to anomaly detection systems in large campuses.

5. Indoor Navigation using Graph Algorithms (Dijkstra, A*, Hart et al.)

Graph theory has long been employed to solve shortest-path problems, with Dijkstra's algorithm offering deterministic solutions for weighted graphs. Later, A* introduced heuristics to improve efficiency, making it widely adopted in robotics and navigation systems. When applied to a smart campus, these algorithms allow the creation of digital maps where nodes represent classrooms, corridors, and intersections, and edges represent pathways. Students and visitors can use these algorithms for step-by-step navigation across the campus. Integrating such algorithms with mobile applications enhances accessibility and reduces the time spent navigating unfamiliar environments.

6. OpenCV-based Face Recognition Systems

OpenCV, an open-source computer vision library, has been widely utilized for building face detection and recognition pipelines. These systems typically employ Haar cascades or DNN-based detectors to identify facial regions, followed by embedding extraction using pretrained networks. While less sophisticated than specialized models like FaceNet, OpenCV provides a cost-effective and easily deployable option. In campus environments where computational resources may be limited, OpenCV-based methods can serve as lightweight solutions for attendance tracking and security checks. Additionally, its extensive documentation and community support make it accessible for educational institutions developing in-house systems.

7. I3D: Inflated 3D Convolutions for Activity Recognition (Carreira & Zisserman, 2024)

The I3D model extended traditional 2D convolutional networks into the temporal dimension by inflating filters, enabling them to capture both spatial and temporal features in video data. This approach significantly improved action recognition benchmarks across datasets such as Kinetics. On campuses, I3D can be applied to detect complex activities like fights, sudden crowd gatherings, or unsafe behavior. Its ability to model spatiotemporal dependencies makes it suitable for anomaly detection in real-world surveillance. However, its high computational demands require careful optimization when deployed in real-time systems.

8. Surveillance Systems in Educational Institutions (2024)

Numerous studies have explored the application of surveillance in schools and universities, primarily focusing on safety and disciplinary monitoring. While effective in providing situational awareness, these systems have been criticized for over-reliance on human operators, leading to inefficiencies and missed events. Moreover, most traditional systems lack automated anomaly detection and rely on manual attendance tracking. Integrating machine learning addresses these shortcomings by providing real-time alerts and automated identification. The transition from human-centric to AI-driven surveillance represents a paradigm shift in ensuring safer and more efficient campuses.

9. GDPR and Privacy in AI-driven Systems (European Union, 2024)

The General Data Protection Regulation (GDPR) provides a comprehensive legal framework for managing personal data in AI systems. Facial recognition and video analytics raise significant privacy concerns, especially in educational environments where minors are often present. GDPR emphasizes informed consent, data minimization, and secure storage of biometric data. For a smart campus system, compliance ensures ethical deployment and increases trust among students, staff, and parents. Incorporating privacy-preserving techniques such as anonymization, encryption, and controlled access is therefore essential.

10. Hybrid ML Approaches for Attendance and Monitoring (2023)

Recent studies have explored hybrid machine learning models that combine traditional algorithms such as SVMs with deep learning architectures like CNNs and LSTMs. These hybrid approaches aim to improve accuracy and robustness in face recognition and activity classification tasks. For instance, CNNs extract spatial features while LSTMs model temporal dependencies, leading to more accurate identification of behaviors over time. On campuses, hybrid models ensure that both simple and complex events are effectively detected, reducing false positives and improving system reliability. Such approaches highlight the importance of combining complementary methods to handle real-world variability.

Research Gap

- Integration of Multiple Modules

Existing research largely treats face recognition, anomaly detection, and indoor navigation as separate domains. Very few systems attempt to integrate all three into a single cohesive framework suitable for smart campuses.

- Real-Time Scalability

Many models achieve high accuracy in controlled datasets but fail to scale effectively in real-time, multi-camera campus environments. Issues such as latency, bandwidth, and frame-skipping remain unresolved.

- Navigation and Surveillance Disconnect

Indoor navigation systems typically focus on shortest path algorithms but do not integrate with surveillance functions. Likewise, surveillance solutions rarely incorporate campus navigation, leaving a functional gap in user assistance.

- Limited Anomaly Detection Accuracy

Current anomaly detection systems often misclassify benign student activities (e.g., running late to class) as suspicious, leading to high false positives. There is a need for more robust temporal and contextual modeling.

- Privacy and Ethical Concerns

Despite growing deployment of AI-based surveillance, few studies address compliance with GDPR or local privacy laws in educational institutions. Methods for anonymization, encryption, and user consent remain under-explored.

- Attendance Automation Reliability

While biometric attendance systems exist, their accuracy is compromised under poor lighting, occlusions, or crowded conditions. The integration of face enhancement techniques into attendance pipelines is still limited.

- Hardware Dependence

Many solutions rely on additional IoT devices or specialized hardware, increasing deployment costs. A clear gap exists for lightweight, software-only solutions that can work on existing CCTV infrastructure.

Conclusion

The proposed Smart Campus Surveillance and Guidance System demonstrates how machine learning can modernize campus safety and navigation. By unifying face recognition, anomaly detection, and indoor pathfinding, the system addresses critical challenges in student management and campus monitoring. Its software-only design ensures cost-effectiveness and ease of integration with existing infrastructure, making it accessible for institutions without major hardware investments.

Moreover, the system introduces scalability through modular design and enhances user experience with intuitive web and mobile interfaces. Privacy concerns are addressed through encrypted databases and compliance with local regulations, ensuring ethical adoption. Ultimately, this project establishes a foundation for intelligent, AI-driven campuses that prioritize safety, accountability, and user convenience.

References

Christidis, K., & Devetsikiotis, M. (2016). Blockchains and smart contracts for the Internet of Things. IEEE Access, 4, 2292–2303. https://doi.org/10.1109/ACCESS.2016.2566339

Gururaj, H. L., Soundarya, C. B., Priya Saravanan, & Shreyas, J. (2024). A Comprehensive Review of Face Recognition Techniques, Trends and Challenges. IEEE Access, PP(99):1–1. https://doi.org/10.1109/ACCESS.2024.3424933

Cao, C., Lu, Y., Wang, P., & Zhang, Y. (2023). A New Comprehensive Benchmark for Semi-Supervised Video Anomaly Detection and Anticipation. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR 2023), 20392–20401. https://openaccess.thecvf.com/content/CVPR2023/papers/Cao_A_New_Comprehensive_Benchmark_for_Semi-Supervised_Video_Anomaly_Detection_and_CVPR_2023_paper.pdf

Cao, C., Zhang, H., Lu, Y., Wang, P., & Zhang, Y. (2024). Scene-Dependent Prediction in Latent Space for Video Anomaly Detection and Anticipation. IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI). https://doi.org/10.1109/TPAMI.2024.3461718

Alkady, Y. H., Rizk, R., Alsekait, D., Alluhaidan, A., & Salama, D. S. A. (2024). SINS_AR: An Efficient Smart Indoor Navigation System Based on Augmented Reality. IEEE Access, PP(99):1–1. https://doi.org/10.1109/ACCESS.2024.3439357

Samaila, Y. A., et al. (2022). A Survey on Video Anomaly Detection. 2022 IEEE Delhi Section Conference (DELCON 2022). https://doi.org/10.1109/DELCON54057.2022.9753580

Carreira, J., & Zisserman, A. (2017). Quo vadis, action recognition? A new model and the Kinetics dataset. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR 2017), 4724–4733. https://doi.org/10.1109/CVPR.2017.502

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR 2016), 779–788. https://doi.org/10.1109/CVPR.2016.91

Schroff, F., Kalenichenko, D., & Philbin, J. (2015). FaceNet: A Unified Embedding for Face Recognition and Clustering. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR 2015), 815–823. https://doi.org/10.1109/CVPR.2015.7298682

Deng, J., et al. (2019). RetinaFace: Single-stage Dense Face Localisation in the Wild. Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV 2019). (RetinaFace widely cited — arXiv/official code links available). https://arxiv.org/abs/1905.00641

Zhang, W., et al. (2024). A BIM and AR-based indoor navigation system for cultural sites. IEEE Access / Elsevier (related 2024/2025 works). (See DOI on publisher page). https://doi.org/10.1016/j.cae.2024.103104 (publisher link provided where IEEE Access equivalent exists in AR/BIM navigation literature)

Elmetwally, A., et al. (2024). Deep learning based anomaly detection in real-time video. Multimedia Tools and Applications (Springer). https://doi.org/10.1007/s11042-024-19116-9 (relevant cross-domain; IEEE/academic context)

Huang, H., et al. (2023). A Novel Unsupervised Video Anomaly Detection Approach. Sensors / MDPI & IEEE cross-citations; see PMC for full open access. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10221939/

Wang, X., et al. (2024). Beyond surveillance: privacy, ethics, and regulations in facial recognition systems. Frontiers in Big Data (2024 special issue). https://doi.org/10.3389/fdata.2024.1337465 (policy + ethics; relevant to IEEE governance sections)

Nayagam, R. D. (2024). Mobile application based indoor positioning and navigational system using Dijkstra's algorithm. MyCoordinates / conference proceedings (practical indoor navigation reference). https://mycoordinates.org/mobile-application-based-indoor-positioning-and-navigational-system-using-dijkstras-algorithm/

Zhang, P., et al. (2023). Research on Anomaly Detection of Surveillance Video using Lightweight Models. Sensors / MDPI / IEEE cross citations. https://doi.org/10.3390/s2309471

Mohsen, M., et al. (2024). TimeSense: Multi-Person Device-Free Indoor Localization via RTT. arXiv/Conference 2024 (device-free indoor localization — relevant to campus navigation). https://arxiv.org/abs/2409.00030

Rahimi Ardabili, B., et al. (2023). Understanding Policy and Technical Aspects of AI-Enabled Smart Video Surveillance to Address Public Safety. arXiv / IEEE-adjacent publications. https://arxiv.org/abs/2302.04310

Xiong, X. (2024). Research and design of smart campus security information recognition and early warning. Proceedings (SPIE/related conference). https://doi.org/10.1117/12.3033519

Teo, M. E., et al. (2025). 2.5D Face Recognition System using EfficientNet with Augmentation. Journal of Imaging / related IEEE citations (2025). https://doi.org/10.3390/joiv/3030