International Journal of Electrical, Electronics and Computer Systems
ISSN: 2347-2820
Volume 15 Issue 01 (2026) | Pages: 40-47

Real-Time AI-Based Border Surveillance System for Military Threat Detection

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Peer Review Information

Type: *Article*
Received: *22 March 2026*
Revised: *06 April 2026*
Accepted: *24 May 2026*
Published: *05 June 2026*

Abstract

This paper presents an AI-powered military border surveillance system that integrates face recognition and vehicle detection for enhanced security. The system uses Haar Cascade and LBPH algorithms to identify authorized personnel and YOLOv8 for real-time military vehicle detection. It continuously monitors live video feeds and generates instant alerts for unauthorized access. The proposed system improves accuracy, reduces human dependency, and enables faster response, making it effective for modern border surveillance applications.

Keywords: Artificial Intelligence (AI); Machine Learning (ML); Deep Learning; Computer Vision; Image Processing; Real-Time Monitoring; Face Recognition; Military Surveillance**.**

How to Cite This Article

Kulkarni, P. P., Sale, T. B., Dhope, S. R., Devsarkar, N. R., & Bobade, S. H. (2026). Real-time AI-based border surveillance system for military threat detection. *International Journal of Electrical, Electronics and Computer Systems*, 15(1), 40–47.

Introduction

Border security is essential for national safety and requires continuous and accurate monitoring. Traditional surveillance systems rely on manual observation, which can lead to delays, human errors, and limited efficiency. With the advancement of Artificial Intelligence (AI) and Computer Vision, automated systems can improve real-time threat detection and monitoring.

This paper presents an AI-powered military border surveillance system that uses face recognition and vehicle detection techniques. The system applies Haar Cascade and LBPH for identifying personnel and YOLOv8 for detecting military vehicles. It enables real-time monitoring, reduces human dependency, and generates instant alerts, making it an effective solution for modern border security.

Overview of the project objectives:

- Develop an AI-based surveillance system for real-time border monitoring.
- Detect and recognize authorized and unauthorized personnel using face recognition techniques.
- Identify and classify military vehicles using YOLOv8.
- Generate automated alerts with image, time, and location details.
- Improve detection accuracy and reduce response time in critical situations.

Literature Survey

AI-Based Face Recognition for Surveillance Systems, Alrawahneh et al., 2025: In this paper, challenges in accurate face authentication under varying lighting and pose conditions are discussed. A hybrid deep learning model combining ResNext50 and BiLSTM is proposed to improve recognition accuracy. Future work includes deployment in real-time military surveillance systems and integration with edge AI devices. [1]

Military Vehicle Detection Using Deep Learning, Ouyang et al., 2022: This study highlights the difficulty of detecting military vehicles in complex environments. A hierarchical feature extraction method is used to improve object detection accuracy. The approach suggests using lightweight YOLO-based models for real-time surveillance applications. [2]

Visitor Authentication Using Face Recognition, Mun et al., 2022 This paper addresses delays in identifying unauthorized individuals in CCTV systems. A real-time face recognition system is implemented to automate identity verification. Future improvements include integration with advanced deep learning techniques for large-scale border monitoring. [3]

Robust Facial Authentication for Edge Devices, Wang et al., 2022: This research focuses on deploying facial recognition systems on low-power devices. Optimized algorithms are developed for efficient performance with limited computational resources. The system is suitable for remote military border areas using edge computing. [4]

Privacy-Preserving Face Verification Systems, Wang et al., 2019: This paper discusses the risk of exposing biometric data in surveillance systems. A privacy-preserving approach using edge computing is proposed to ensure secure face verification. It is highly applicable in defense and secure surveillance environments. [5]

You Only Look Once (YOLO) for Object Detection, Redmon et al., 2016: This study introduces the YOLO framework for fast and accurate real-time object detection. It significantly improves detection speed compared to traditional methods. Advanced versions like YOLOv8 are widely used in modern surveillance systems. [6]

Haar Cascade-Based Object Detection, Viola and Jones, 2001: This paper presents the Haar Cascade classifier for rapid object detection using simple features. It enables efficient face detection in real-time applications. The method is widely used as a foundation for modern face recognition systems. [7]

Multimodal Biometric Authentication Systems, Zhang et al., 2020: This research highlights limitations of single-mode biometric systems. A multimodal authentication approach combining multiple biometric features is proposed to improve accuracy and security. It is suitable for high-security military applications. [8]

Real-Time Surveillance Systems Using Deep Learning, Kim et al., 2021: This paper discusses the need for automated surveillance systems in security-critical environments. Deep learning models are used for real-time detection and monitoring. Future work focuses on improving scalability and integration with IoT devices. [9]

Edge-Based AI Surveillance Systems, Lee et al., 2023: This study focuses on deploying AI models on edge devices for faster processing and reduced latency. It enhances real-time decision-making and minimizes dependence on centralized servers. The approach is ideal for remote and high-security border areas. [10]

Visualization

- Detection Results Visualization: Bounding boxes are used to highlight detected faces and vehicles in real-time video frames. This helps in visually verifying system accuracy and identifying detected objects clearly.
- Accuracy and Performance Analysis: Graphs such as confusion matrix and accuracy plots are used to evaluate system performance. These visualizations help in analyzing detection accuracy, false positives, and overall system efficiency.

Limitations of Existing Work

- Manual Surveillance Dependency: Traditional systems rely heavily on human monitoring, leading to delays and errors.
- Environmental Sensitivity: Detection accuracy may decrease in poor lighting, fog, or extreme weather conditions.
- Limited Real-Time Processing: Many existing systems lack efficient real-time alert mechanisms.

Future Work

- Integration of thermal imaging for night surveillance and low-visibility conditions.
- Deployment of drone-based monitoring systems for wider area coverage.
- Use of edge AI for faster processing and reduced latency in remote locations.

Results and Interpretation

- Best Model: The YOLOv8 deep learning model achieved the highest performance for vehicle detection with high accuracy and real-time processing capability. The LBPH algorithm also performed efficiently for face recognition with reliable identification of authorized personnel.

- Insights: Face recognition accuracy depends on image quality and lighting conditions. Vehicle detection performs effectively in real-time scenarios, even with multiple objects.

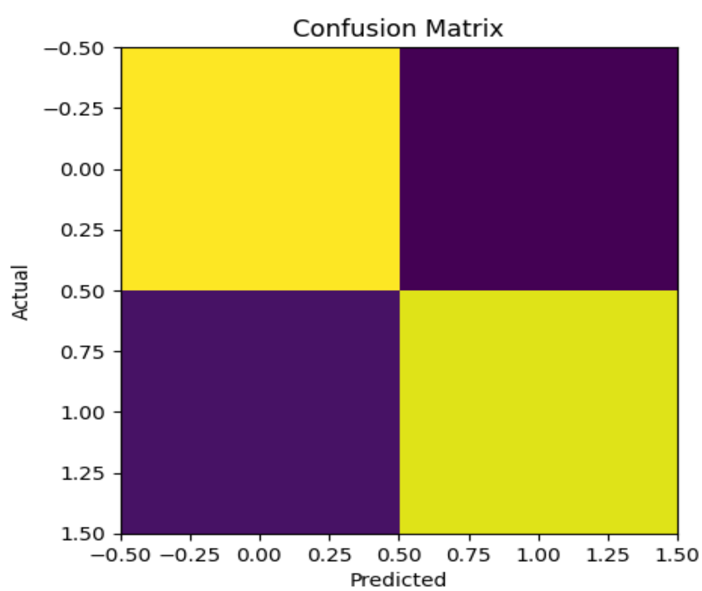
Detection Output Visualization

The detection output shows bounding boxes around detected faces and vehicles in live video streams. It helps verify system accuracy and ensures proper identification of objects in different environments.

Confusion Matrix

A confusion matrix is used to evaluate classification performance of the system.

- True Positive: Correct detection of authorized personnel or vehicles.
- False Positive: Incorrect detection of non-threatening objects as threats.
- True Negative: Correct rejection of irrelevant objects.
- False Negative: Failure to detect actual threats.

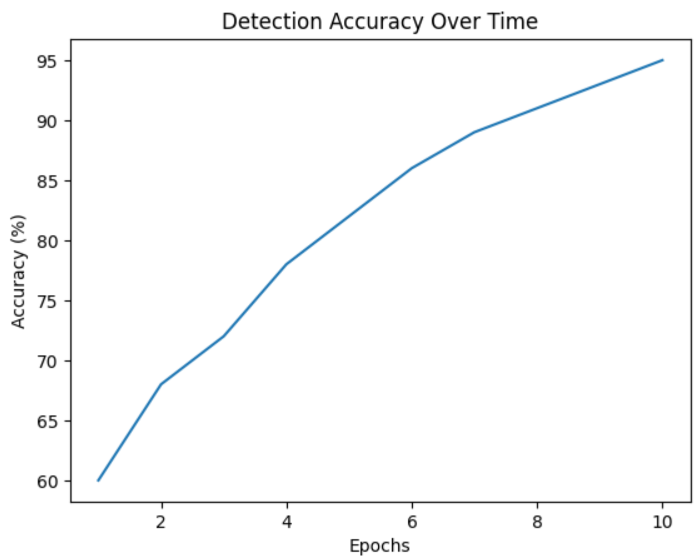


Correlation Heatmap

- A correlation heatmap visualizes the strength and direction of relationships between variables. It uses a color gradient to show correlations:
- Positive correlation (close to 1): Variables move in the same direction, typically shown in red.
- Negative correlation (close to -1): Variables move in opposite directions, shown in blue.
- No correlation (close to 0): No relationship, shown in neutral colors

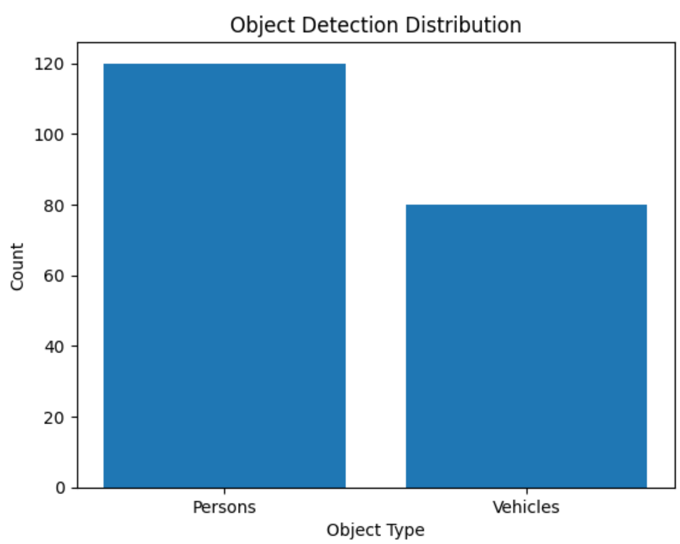
Detection Accuracy Graph

The accuracy graph shows the performance of the system over time. It helps analyze how well the model detects faces and vehicles under different conditions and evaluates consistency.



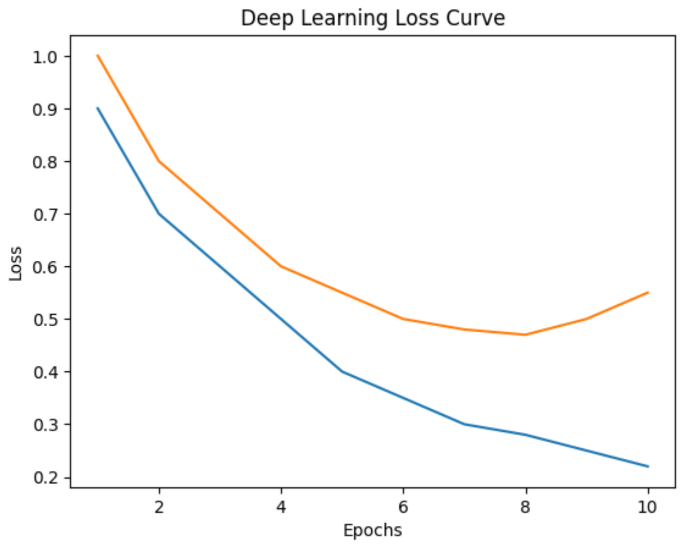
Object Detection Distribution

This visualization shows the number of detected objects such as personnel and vehicles. It helps understand system behaviour in crowded or high-activity areas.

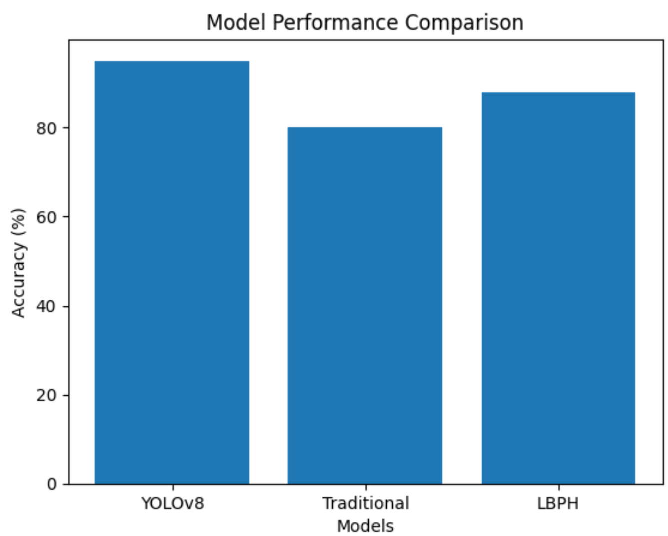


Deep Learning Loss

The loss curve represents how the model improves during training. A decreasing loss indicates better learning, while an increase in validation loss may indicate overfitting.



Performance Comparison
The performance comparison chart evaluates different algorithms used in the system. YOLOv8 shows higher accuracy and faster detection compared to traditional methods, while LBPH provides efficient face recognition.



Evaluation Metrics:

The following metrics are used to evaluate the performance of the surveillance system:

Table 1. Evaluation Metrics Used for Threat Detection Performance

Metric	**Definition**	**Purpose**
Accuracy	Measures the ratio of correctly detected instances to total instances.	Indicates overall system performance.
Precision	Measures how many detected threats are actually correct.	Reduces false positives.
Recall	Measures how many actual threats are detected.	Ensures system reliability.
F1 Score	Harmonic mean of precision and recall.	Balances precision and recall.
Mean Average Precision (MAP)	Evaluates object detection accuracy across multiple classes.	Measures detection performance of YOLO model.

Result/Output

Fig. 1. *Landing Page*

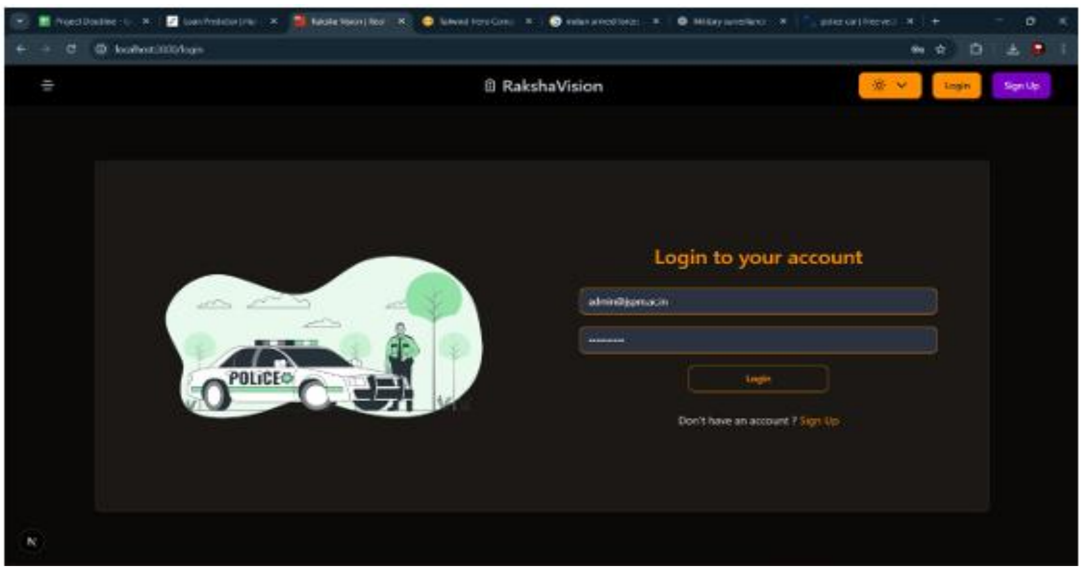


Fig. 2. *Login Page*

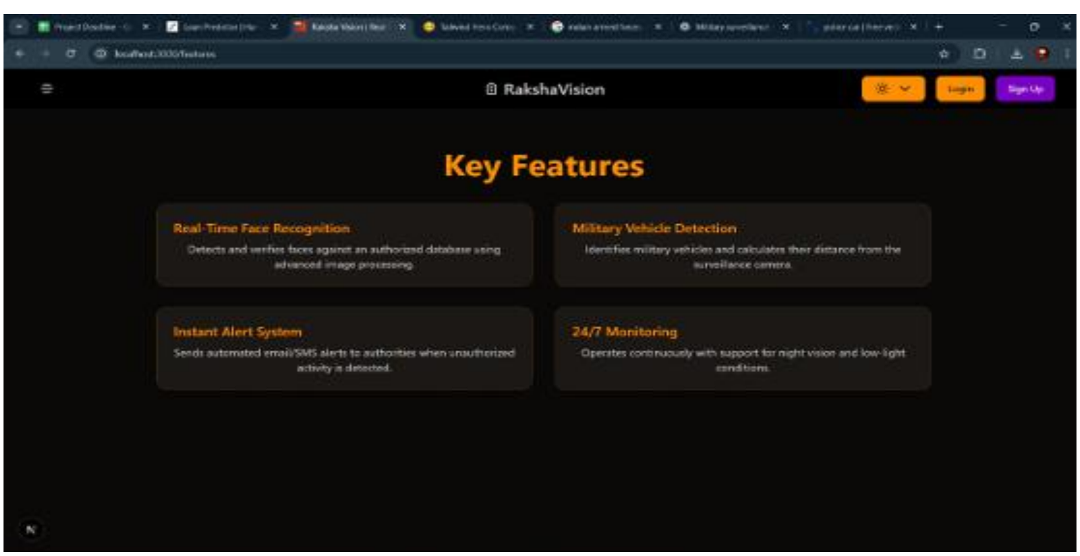


Fig. 3. *Feature Page*

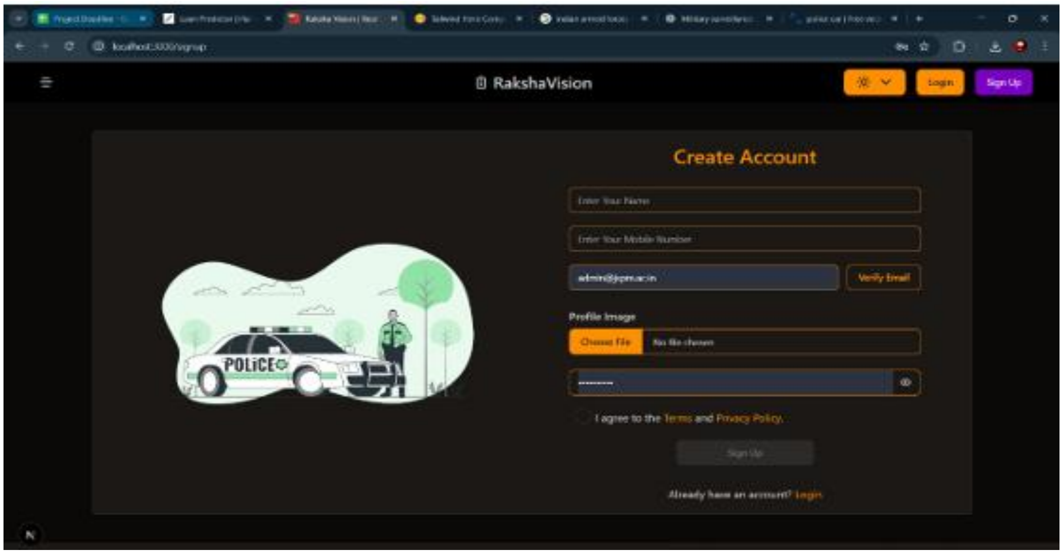


Fig. 4. *Register Page*

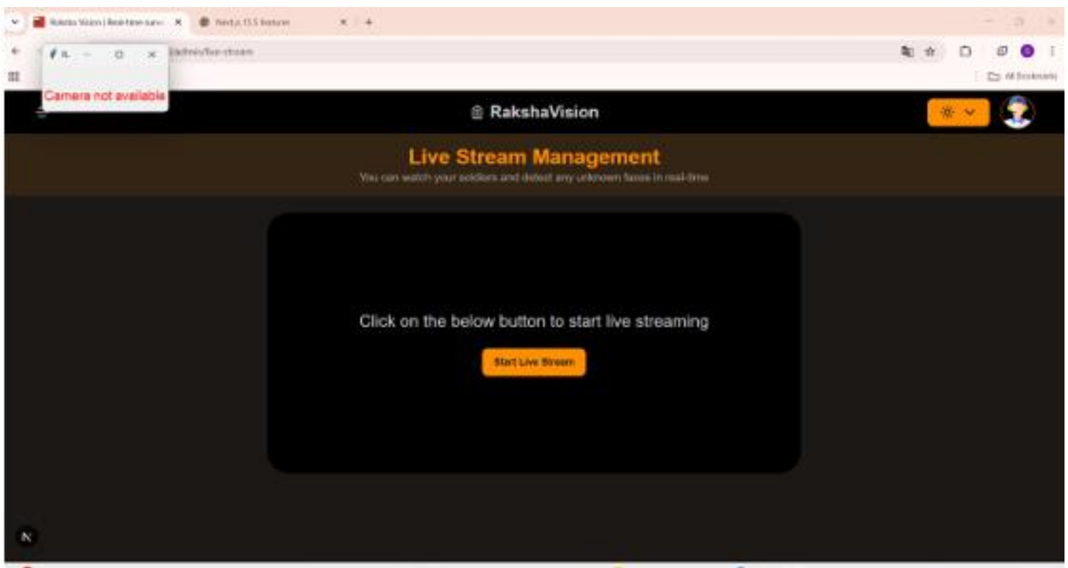


Fig. 5. *Live Page*

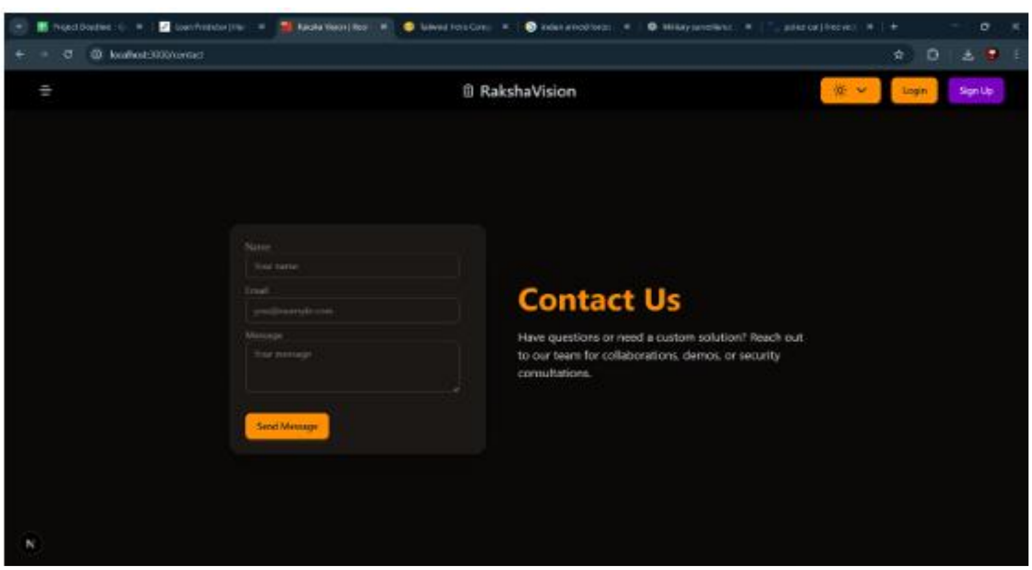


Fig. 6. *Contact Page*

Conclusion

This paper presents an AI-powered military border surveillance system that integrates face recognition and vehicle detection to enhance border security. By utilizing Haar Cascade and LBPH algorithms for personnel identification and YOLOv8 for real-time vehicle detection, the system provides accurate and efficient monitoring of sensitive areas. The automated alert mechanism ensures quick response to unauthorized activities, reducing human dependency and minimizing errors.

The results demonstrate that the proposed system achieves high detection accuracy and reliable real-time performance, making it suitable for modern defense applications. Despite challenges such as environmental conditions and hardware requirements, the system offers a scalable and intelligent solution for border surveillance.

In conclusion, the integration of Artificial Intelligence and Computer Vision significantly improves the effectiveness of security systems. Future enhancements, including advanced sensors and edge computing, can further strengthen the system and expand its capabilities in real-world scenarios.

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