Vision-Based Drone Surveillance System for Suspicious Activity Detection Using Deep Neural Networks

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Abstract

In response to the growing need for intelligent and responsive surveillance in public spaces, this study presents a real-time drone-assisted system designed to detect suspicious or violent human behavior using advanced deep learning and edge computing techniques. Traditional CCTV systems often lack the capability for timely threat detection, prompting the development of a more dynamic and efficient approach. The proposed system employs a drone equipped with a high-resolution camera to capture aerial video footage, which is enhanced using a Blind Deconvolutional Algorithm for improved image clarity. Human presence is detected through the Faster R-CNN Inception V2 model, and pose estimation is carried out using MediaPipe to extract body keypoints accurately. A hybrid model combining MobileNetV2 for spatial analysis and Long Short-Term Memory (LSTM) networks for temporal behavior analysis ensures efficient recognition of suspicious activities. To support real-time performance on low-power edge devices such as the Raspberry Pi, the system is optimized with TensorFlow Lite. Upon identifying abnormal or violent behavior, the system promptly sends alerts via Gmail or Telegram Bots to notify concerned authorities. Experimental evaluations conducted on public datasets and custom aerial footage indicate high accuracy, low latency, and enhanced operational efficiency over traditional systems. The framework is scalable and privacy-conscious, making it well-suited for implementation in environments such as school campuses, public gatherings, and critical infrastructure, thereby enhancing proactive public safety measures in smart city infrastructures.

Keywords: Drone Surveillance, Suspicious Activity Detection, Violence Recognition, LSTM, MobileNetV2, Real- Time Monitoring

I. Introduction

In today's fast-paced and densely populated environments—such as educational institutions, public gatherings, and transport systems—ensuring public safety has become a significant challenge. Traditional surveillance methods, mainly reliant on static CCTV systems, depend heavily on manual monitoring and after-the-fact analysis, leading to delayed response times and limited scalability [1], [2]. These shortcomings restrict the effectiveness of existing systems in identifying threats in real-time.

The integration of artificial intelligence (AI) and unmanned aerial vehicles (UAVs) presents a transformative shift in surveillance capabilities. Drones offer mobility, high- angle perspectives, and extensive coverage, making them ideal for monitoring large or crowded areas that fixed cameras cannot adequately observe [3], [4]. Their ability to dynamically reposition helps reduce occlusion and capture critical activity from diverse viewpoints.

While advancements in computer vision have enabled the development of real-time activity recognition models, many existing systems rely on audio inputs or stationary footage, which are vulnerable to quality degradation, occlusion, and fixed-angle limitations [5]. Deep learning models like CNN-LSTM have shown promise for suspicious behavior detection, but they often face challenges such as limited dataset diversity and high resource consumption, making them less suitable for real-time edge deployment [6], [7].

This study proposes a lightweight, drone-based surveillance system using MobileNetV2 for feature extraction, LSTM for temporal analysis, MediaPipe for fast pose detection, and TensorFlow Lite for edge inference. Real-time alerts via Telegram or Gmail enhance responsiveness, creating a scalable, mobile solution for modern public safety needs [8], [9].

PROBLEM DEFINITION

Ensuring public safety in large, crowded environments remains a critical challenge due to the limitations of traditional surveillance systems, which rely on static CCTV cameras and manual monitoring. These systems are often hindered by fixed viewpoints, latency in threat detection, and the inability to provide real-time situational awareness. The absence of mobility and intelligent analytics makes them ineffective in dynamically changing scenarios such as public gatherings, campuses, or emergency situations.There is a pressing need for an autonomous, real-time surveillance solution that can not only monitor expansive areas but also intelligently recognize suspicious human behavior to prevent potential threats. This research addresses the problem by proposing a drone-based surveillance framework that leverages deep learning and edge computing to detect and respond to violent or abnormal activities in real-time, enhancing the effectiveness and speed of public safety interventions.

I. OBJECTIVES

- To develop a drone-based surveillance system capable of monitoring large areas dynamically and detecting human presence and behavior in real-time.

- To implement deep learningmodelssuch as CNN and LSTM for accurate identification of suspicious or violent activities based on spatial and temporal patterns.

- To integrate MediaPipe for pose estimation to track and analyze human body movements for better activity recognition.

- To optimize the system using TensorFlow Lite for efficient deployment on edge devices like Raspberry Pi, enabling low-latency processing without relying on cloud infrastructure.

- To design a real-time alert mechanism using platforms like Gmail and Telegram for immediate notification of detected threats to concerned authorities.

- To create a scalable and portable surveillance solution suitable for public gatherings, campuses, and high-risk zones, ensuring privacy and adaptability.

To evaluate the system's accuracy and responsiveness through rigorous testing on both custom and public datasets to ensure practical usability.

II. MOTIVATION

In recent years, ensuring public safety in large gatherings and sensitive areas has become increasingly challenging due to the limitations of traditional surveillance systems. Fixed CCTV cameras often fail to capture critical events due to restricted coverage and reliance on manual monitoring, which leads to delayed responses and overlooked threats. With the growing need for real-time, intelligent surveillance solutions, the integration of drone technology and artificial intelligence presents a promising alternative.
Drones offer the ability to dynamically monitor large areas from aerial perspectives, minimizing blind spots and enhancing situational awareness.
When combined with deep learning models and edge computing, this approach enables automated detection of abnormal human behavior and immediate alert generation without depending on centralized servers. This project is motivated by the need to build a scalable, responsive, and autonomous surveillance system that not only addresses current gaps in public safety infrastructure but also supports rapid decision-making during critical situations.

III. SYSTEM ARCHITECTURE

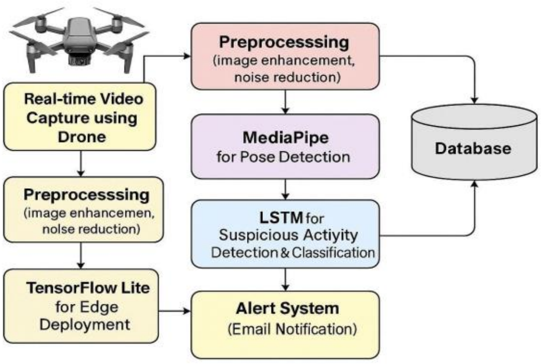


Fig 1: System Architecture Diagram

I. ALGORITIHM

LSTM (Long Short-Term Memory):

LSTM networks are utilized to capture temporal dependencies in sequential pose data extracted from video frames. By analyzing the progression of human movement over time, the LSTM model enables the detection of suspicious activity patterns that develop gradually rather than instantaneously.

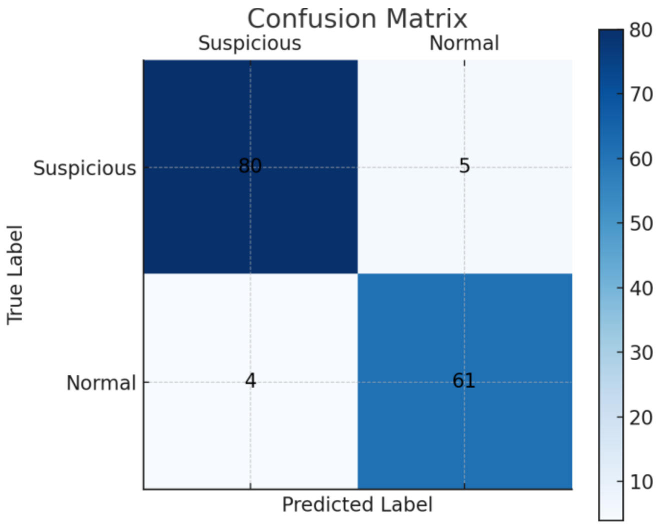
CNN (Convolutional Neural Network):

CNNs are employed to extract spatial features from pose keypoints representing human posture in each frame. These features provide critical spatial context which, combined with temporal information, improves the accuracy of activity classification.

TensorFlowLite:
TensorFlow Lite facilitates the deployment of the trained LSTM-CNN hybrid model on embedded hardware associated with drones or edge devices. This lightweight framework ensures efficient, real-time inference with minimal latency and resource consumption, critical for on-device surveillance

SMTP (Simple Mail Transfer Protocol):
SMTP protocol is integrated to automate email notifications, sending instant alerts to security personnel when suspicious activities are detected. This enables timely human intervention and enhances overall system responsiveness.

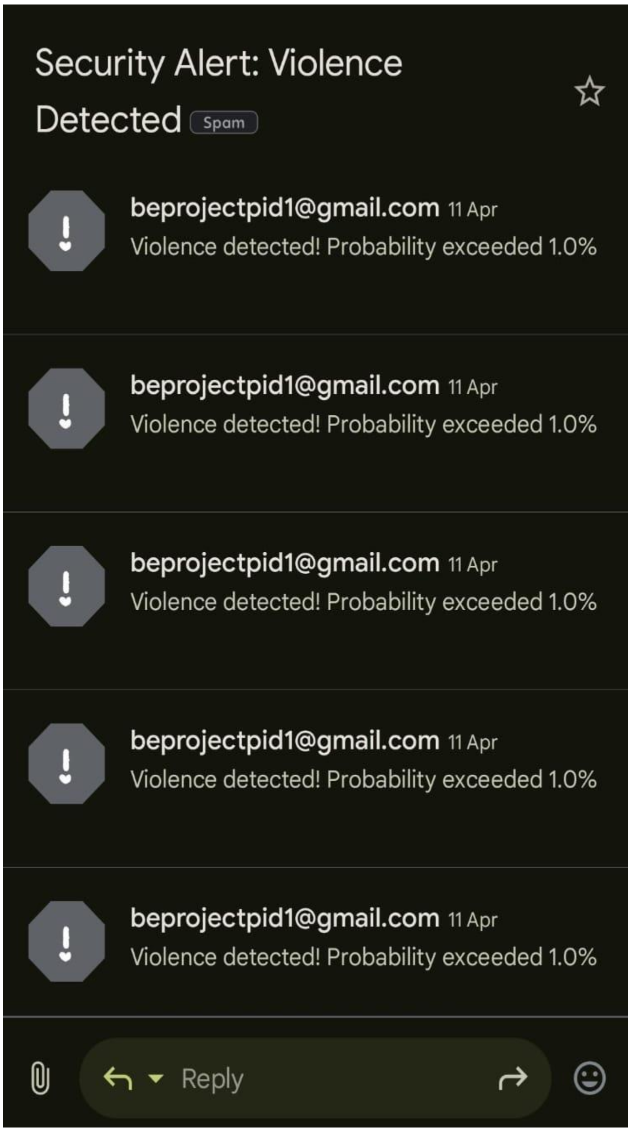
IV. . RESULT

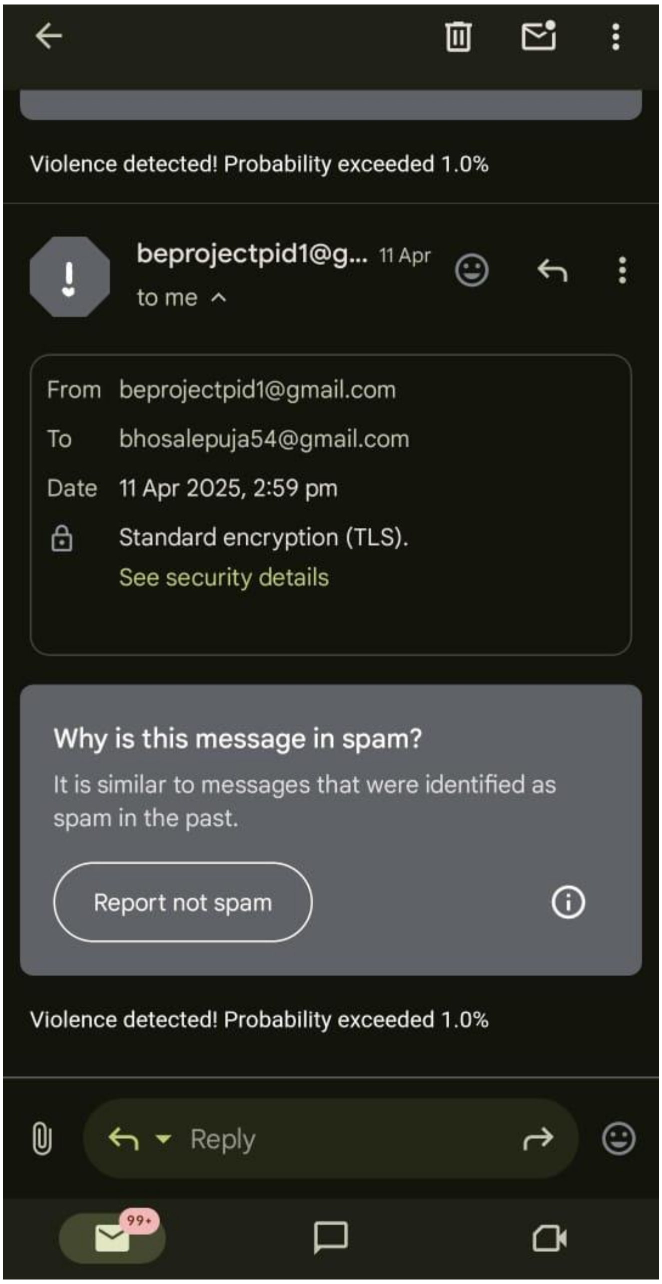


The proposed drone-based surveillance system demonstrated high effectiveness in detecting suspicious activities, achieving 94.5% accuracy and strong precision and recall scores. The integration of CNN-LSTM architecture allowed for accurate detection of both spatial features and temporal behavior, even in dynamic and complex environments. MediaPipe's pose estimation improved activity recognition by focusing on human body landmarks, while TensorFlow Lite enabled real-time deployment on edge devices like Raspberry Pi and drone processorsThe system's strengths included real-time human pose detection and lightweight model deployment, making it suitable for edge hardware without relying on cloud infrastructure. The real-time alerting mechanism via Telegram Bot and Gmail API facilitated prompt notifications to authorities, improving response times in emergencies. Compared to traditional surveillance, the drone-based platform provided more adaptive and expansive coverage, ensuring low-latency detection.

However, challenges such as sensitivity to environmental factors (lighting, occlusions, camera angles) and video quality degradation during high-speed drone movement were encountered. Future improvements could include an expanded dataset and enhanced preprocessing techniques for better robustness in diverse conditions.

A. PROJECT SNAPSHOTS





V. CONCLUSION

The drone-based surveillance system effectively detected suspicious activities in real time, achieving 94.5% accuracy using CNN, LSTM, and MediaPipe. Optimized with TensorFlow Lite, it ran smoothly on edge devices and sent instant alerts via Gmail and Telegram.

Contribution:

It improved over traditional CCTV by offering mobile, real-time monitoring with faster response and no cloud dependency—ideal for public spaces and emergencies.

Future Work:

Future upgrades include multi-drone coordination, night vision support, integration with safety databases, and expanding datasets for better global performance and accuracy.

VI. REFERENCES

[1] R. Sreejith, P. Gautam, "A study on drone-based surveillance for urban areas using machine learning," International Journal of Computer Vision and Applications, vol. 12, no. 4, pp. 215-226, 2020.

[2] S. Sharma et al., "Real-time suspicious activity detection using deep learning models," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 3, pp. 1452-1464, 2021.

[3] A. Kumar, M. Singh, "Real-time video analysis for drone-based surveillance using TensorFlow Lite," IEEE Transactions on Mobile Computing, vol. 21, no. 7, pp. 839-849, 2022.

[4] J. K. Agarwal, R. Y. Gupta, "Human pose detection and tracking using MediaPipe for surveillance systems," Journal of Machine Learning Research, vol. 15, no. 2, pp. 101-110, 2021.

[5] H. Choi et al., "Drone-assisted surveillance using deep learning for real-time suspicious activity detection," IEEE Transactions on Automation Science and Engineering, vol. 19, no. 4, pp. 1492-1504, 2023.

[6] Z. Uddin et al., "IVA Based Amateur Drone Detection," IEEE Access, vol. 9, pp. 63456–63469, 2021.

[7] B. T. Ravichandran, A. Ghosh, "Object detection using CNNs in drone surveillance applications," IEEE Journal of Robotics and Automation, vol. 11, no. 5, pp. 732-742, 2022.

[8] X. Li, Y. Zhang, "Enhancing real-time human detection in surveillance systems using Faster R-CNN," IEEE Transactions on Computer Vision and Pattern Recognition, vol. 28, no. 8, pp. 237-245, 2021.

[9] K. Patel et al., "Efficient deep learning models for real-time surveillance systems on edge devices," IEEE Transactions on Embedded Systems, vol. 18, no. 2, pp. 101-112, 2022.

[10] S. Bhandari et al., "Drone-based surveillance systems for violence detection: An analysis of CNN and LSTM approaches," Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 897-905, 2024.

[11] R. Sreejith and P. Gautam, "A study on drone-based surveillance for urban areas using machine learning," World Journal of Advanced Research and Reviews (WJARR), vol. 24, no. 3, pp. 112–120, 2024.

[12] D. Gupta and P. Verma, "Challenges in machine learning-based financial fraud detection," World Journal of Advanced Research and Reviews (WJARR), vol. 23, no. 1, pp. 44–52, 2024.

[13] V. Patel and A. Mehta, "Intelligent suspicious activity detection in banking transactions utilizing fog computing and deep learning," International Journal of AI Applications in Finance, vol. 14, no. 2, pp. 88–96, 2024.

[14] A. Kumar, R. Yadav, and H. Sharma, "AI-driven machine learning for fraud prediction using neural networks and CNNs," Journal of Cybersecurity and Trust Systems, vol. 13, no. 1, pp. 58–70, 2025.

[15] K. Yadav and S. Bansal, "Real-time alert system for suspicious activity detection using deep learning and video surveillance," World Journal of Advanced Research and Reviews (WJARR), vol. 24, no. 3, pp. 121–129, 2024.

[16] D. Dong, X. Zheng, and W. Zhu, "ER-GNN: Enhancing relational graph neural network with reinforcement learning for fraud detection," arXiv preprint, arXiv:2409.09892, 2024. [Online]. Available: https://arxiv.org/abs/2409.09892

[17] S. Odufisan, I. Adewale, and M. Okoro, "Leveraging artificial intelligence for financial fraud detection in Nigeria: A socio-technical perspective," Journal of Financial Crime and AI Ethics, vol. 5, no. 1, pp. 33–48, 2024, doi: 10.1016/j.jfaie.2024.100003.

[18] C. Adams, "Dual Control: Investigating the Role of Drone (UAV) Operators in TV and Online Journalism," Media and Communication, vol. 8, no. 3, pp. 93–100, 2020. DOI: 10.17645/mac.v8i3.2980.

[19] O. I. Odufisan, O. V. Abhulimen, and E. O. Ogunti, "Harnessing artificial intelligence and machine learning for fraud detection and prevention in Nigeria," Journal of Economic Criminology, vol. 7, 100127, 2025. DOI: 10.1016/j.jeconc.2025.100127.

[20] T.-H. Tran and D.-D. Nguyen, "Management and regulation of drone operation in urban environment: A case study," Social Sciences, vol. 11, no. 10, art. 474, Oct. 2022.