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Design and Development of AI-Assisted UAV for Smart Campus Crowd Analytics and Anomaly Detection

Sam Philip[1], Dr. Pal Pandian P[2]

[1]CHRIST (Deemed to be University), Bangalore Kengeri Campus, Bangalore, India.
[2]CHRIST (Deemed to be University), Bangalore Kengeri Campus, Bangalore, India.

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Abstract: This paper focuses on a self-sufficient UAV-supported monitoring system that can be used to improve smart campus security through real-time crowd analytics and anomaly detection. The system combines a quadrotor drone with a Pixhawk flight controller, a u-blox M10 GPS module, and a stabilized HD camera with the YOLOv8 deep learning model for human detection. It detects unusual activities such as crowd rushes, unauthorized presence, and abnormal dispersion. GPS-based geofencing is used to control patrols within specific areas, while aerial video is streamed to an edge AI processing unit. In trials, over 92% detection accuracy was achieved with highly responsive alerts. The system is modular, scalable, and adaptable to other enclosed environments, providing proactive situational awareness.

Keywords: UAV monitoring, smart campus, crowd analytics, anomaly detection, YOLOv8, geofencing, edge AI, Pixhawk, real-time monitoring, computer vision, autonomous navigation, aerial video processing, human detection, drone-based security.

INTRODUCTION

The breakthrough in the use of Unmanned Aerial Vehicles (UAVs) and the development of Artificial Intelligence (AI) has transformed surveillance systems into agile, real-time platforms capable of monitoring large and complex sites without the limitations imposed by fixed infrastructure [1][2]. Conventional campus security systems rely heavily on static CCTV cameras and manual monitoring, which suffer from blind spots, limited coverage, and delayed response times, especially in open grounds or crowded places [5].

The incorporation of deep learning-based computer vision into UAV platforms has enhanced their capabilities beyond aerial imaging by enabling onboard object detection, tracking, and behavioral analysis [3][4]. The YOLO ("You Only Look Once") family of models, particularly the latest YOLOv8, has demonstrated very low-latency detection with high accuracy, making it suitable for embedded edge AI devices [7].

This research proposes an AI-assisted UAV surveillance system for smart campus applications. The system integrates autonomous navigation using GPS-based geofencing [6], stabilized high-definition video recording, and YOLOv8 for crowd analytics to identify abnormal crowd behavioral patterns such as sudden crowd formation, unauthorized loitering, and rapid dispersal. Unlike conventional monitoring systems that only detect object presence, the proposed framework is context-aware and capable of anticipating contextual crowd behaviors through data-driven security interventions [8][9].

Experimental trials conducted on a university campus demonstrated that the system achieved detection accuracy exceeding 92%, generated low-latency alerts, and operated reliably under a wide range of environmental conditions, making it a scalable and adaptive solution for smart campus safety.

Related Work

UAV-based surveillance has attracted significant attention because of its flexibility, geographical coverage, and adaptability to dynamic environments. Convolutional Neural Networks (CNNs) have proven effective for real-time object detection using UAV platforms [1][3], while the YOLO family of models has become dominant due to its balance of speed and accuracy [2]. YOLOv3 enabled real-time detection with high frame rates [3], whereas YOLOv5 and YOLOv8 focused on optimization for edge AI devices [7].

Crowd analytics using UAV imagery has been applied in public event monitoring, smart cities, and disaster management [2][6]. GPS-based geofencing has become an important safety feature that restricts UAV flight to predefined areas and prevents unauthorized entry into restricted airspace [6]. However, most existing studies focus primarily on object detection and tracking without incorporating higher-level behavioral analysis.

***Corresponding Author:** Sam Philip

Anomaly detection has mainly been investigated using fixed-camera surveillance systems [8], which are less dynamic than UAV-based platforms. Jetson-based UAV systems have been proposed to reduce inference latency [4], although they often sacrifice real-time crowd behavior modeling. Modular UAV architectures have also been proposed for mission-specific applications [9].

This paper extends previous work by integrating YOLOv8-based human detection with real-time crowd behavior analysis, GPS-based geofenced autonomous flight, and anomaly detection using spatiotemporal movement patterns, all within a unified framework.

OBJECTIVES

The objectives of this research are as follows:

1. Enhance campus security through real-time surveillance of large areas.
2. Monitor crowd gatherings and detect anomalous activities using UAVs.
3. Reduce blind spots compared to fixed CCTV systems.
4. Ensure flight safety through GPS-based geofencing.
5. Enable future upgrades through a modular system architecture.
6. Utilize edge AI processing to generate rapid real-time alerts.

SYSTEM DESIGN AND ARCHITECTURE

The proposed system combines a UAV platform, an edge AI processing unit, and a Ground Control Station (GCS) to provide real-time crowd monitoring.

UAV Platform

Autonomous navigation is controlled by a quadcopter equipped with a Pixhawk flight controller. A u-blox M10 GPS module enables geofencing to ensure flights remain within designated safe zones. An HD camera mounted on a two-axis gimbal captures stabilized aerial video. The modular design allows additional sensors, such as thermal cameras, to be integrated when required.

Ground Control and Edge Processing

Mission planning and live monitoring are performed using QGroundControl software at the Ground Control Station (GCS). Video is streamed to an NVIDIA Jetson edge AI device running YOLOv8, which detects people, estimates crowd density, and identifies anomalies.

Geofencing and Autonomous Flight

GPS-based waypoints are pre-programmed to provide systematic campus coverage. If the UAV moves outside the permitted area, a Return-to-Launch (RTL) command is automatically triggered. The system is also capable of modifying its flight path to investigate detected anomalies.

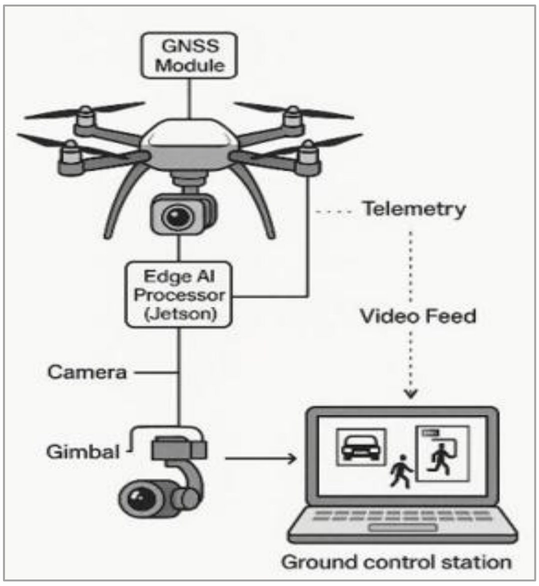

Fig. 1. UAV System Components and Ground Control Communication Overview

METHODOLOGY

The proposed system consists of four principal stages.

Video Recording

A stabilized HD camera records 1080p video at 30–60 fps. The gimbal minimizes motion blur, and the captured video is immediately transmitted to the edge AI processor.

People Detection and Counting

YOLOv8 detects individuals in each frame by generating bounding boxes and confidence scores. These detections are used to estimate crowd density and generate heatmaps.

Anomaly Detection

The system detects anomalous activities such as sudden crowd gatherings, prolonged presence in restricted zones, and rapid evacuation. Rule-based validation and time-based checks are applied to minimize false alarms.

Logging and Communication

Telemetry information is transmitted to the Ground Control Station using the MAVLink protocol. All flight data and detection logs are stored both onboard the UAV and at the GCS for future analysis.

EXPERIMENTAL SETUP AND RESULTS

Test Environment

The UAV system was tested at CHRIST (Deemed to be University), Bangalore Kengeri Campus, across three types of environments:

- **Open Fields** – Large unobstructed spaces such as sports grounds.
- **Semi-Obstructed Zones** – Walkways and courtyards containing trees and buildings.
- **Restricted Areas** – Locations protected by geofenced boundaries, such as hostel entrances.

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Testing was conducted under varying weather and lighting conditions to evaluate system reliability.

Metrics Used

- **Detection Accuracy** – Measured using mAP@0.5 and mAP@0.75.
- **Latency** – Time required from frame capture to detection output.
- **Anomaly Detection Rate (ADR)** – Percentage of actual anomalies correctly detected.
- **False Positive Rate (FPR)** – Percentage of incorrect detections.

RESULTS

On each mission, the UAV flew for **15–25 minutes** based on pre-programmed GPS waypoints. During every operation, the system identified people, tracked them, estimated crowd density, and generated alerts whenever anomalous activities were detected. Performance was compared under open-field and semi-obstructed environments to assess the influence of environmental conditions on the system's accuracy, speed, and reliability. Table 1 presents the experimental results.

Table 1. Comparison of detection accuracy, precision, recall, and F1-score for Open Field and Semi-Obstructed Area environments.

Environment	mAP@0.5 (%)	mAP@0.75 (%)	Latency (ms)	ADR (%)	FPR (%)
Open Field	94.8	92.1	212	93.4	2.9
Semi-Obstructed Area	91.5	88.3	227	90.7	4.6

Key Findings

- Open fields achieved higher accuracy because there were fewer obstructions.
- Latency increased with crowd size, particularly in semi-obstructed areas.
- Most false positives were caused by shadows, glare, or tall structures resembling humans.

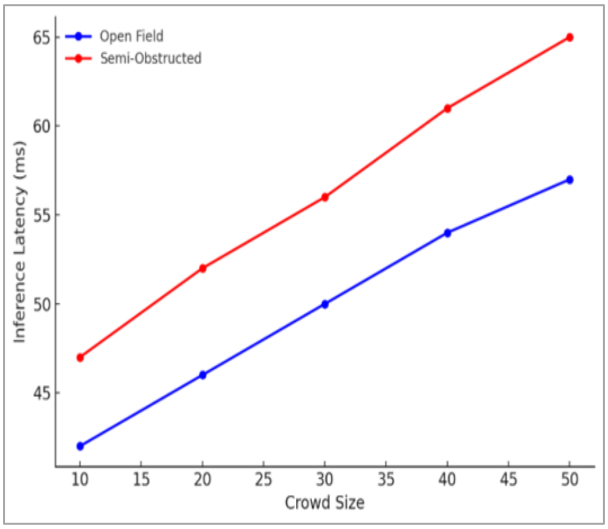

Fig. 2. Impact of increasing crowd size on AI inference latency in Open Field and Semi-Obstructed Area conditions.

Latency increased only marginally with larger crowd sizes and in semi-obstructed environments. Shadows, glare, and the misclassification of objects as people accounted for most of the false positives.

Fig. 3. Depicts a semi-obstructed environment where detection is challenged by partial occlusions; despite this, the system correctly identifies more than 85% of targets.

CHALLENGES

During testing, several challenges were identified:

- **GPS Accuracy** – GNSS signals were less accurate in areas surrounded by tall buildings or dense trees, leading to inaccurate geofence alerts.
- **Weather Conditions** – Strong winds, fog, and low-light conditions reduced image clarity, thereby lowering detection confidence.
- **False Positives** – Shadows, lamp posts, and reflective objects were occasionally misclassified as humans.
- **Edge AI Limitations** – Dense crowd monitoring required high GPU utilization, leading to increased processing delays and reduced flight time.

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Although these challenges did not prevent the system from functioning effectively, they highlight opportunities for future improvements, such as integrating thermal imaging, improved GNSS systems, and optimized AI models.

CONCLUSION

This paper presented the design, development, and validation of an AI-assisted UAV system for real-time crowd monitoring and anomaly detection in a smart campus environment. By integrating a Pixhawk-controlled quadcopter, YOLOv8-based human detection, and GPS-based geofencing, the system achieved low-latency alerts with a detection accuracy exceeding 92%.
The modular architecture enables future hardware upgrades, while edge AI processing ensures rapid detection without requiring continuous cloud connectivity. Field testing demonstrated that the system performed reliably under diverse environmental conditions; however, GPS accuracy limitations, environmental factors, and hardware constraints remain important challenges.
Overall, the proposed system provides a versatile, scalable, and proactive surveillance solution capable of enhancing campus security and situational awareness in educational institutions and similar environments.

FUTURE WORK

The proposed system can be further enhanced through the following improvements:

- **Multi-UAV Coordination** – Deploy multiple drones to provide redundant coverage over larger areas.
- **Night and Low-Light Monitoring** – Integrate thermal or infrared sensors to enable 24-hour surveillance.
- **Predictive Analytics** – Utilize AI models to predict potential anomalies before they occur.
- **Cloud-Edge Integration** – Combine local edge processing with cloud-based analytics for large-scale, multi-location deployments.

These enhancements would increase the operational capability of the system and make it more adaptable to a wide range of security and monitoring applications.

A. Temporal Behavior Modeling for Anomaly Detection

Although the current implementation performs frame-by-frame anomaly detection, future work may incorporate temporal deep learning models such as Long Short-Term Memory (LSTM) networks or transformer-based architectures. These models can learn sequential patterns of crowd behavior over time, enabling the detection of subtle anomalies such as gradual crowd build-up, coordinated group movement, or evolving irregular activities. Incorporating temporal modeling would significantly extend anomaly detection beyond instantaneous event recognition.

B. Federated Learning for Privacy-Preserving Training

A promising extension of this work is the adoption of Federated Learning (FL) to enable collaborative model training across multiple campuses or institutions while preserving data privacy. Instead of centralizing sensitive video data, FL aggregates local model updates generated by UAVs operating in different environments. This decentralized approach preserves privacy while improving model generalization and robustness, making the surveillance platform more scalable across diverse deployment scenarios.

C. Hybrid Sensor Fusion for Low-Light and Occluded Scenarios

To overcome the limitations of relying solely on visual detection, future versions of the system may incorporate multi-sensor fusion by combining RGB video with thermal infrared (IR) sensors. Thermal imaging enhances detection performance under low-light, nighttime, and poor-visibility conditions where conventional cameras are less effective. The fusion of visual and thermal modalities would improve detection robustness and reliability, enabling continuous 24/7 surveillance under challenging environmental conditions.

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