Smart Surveillance System for Detecting Unauthorized Drones in Restricted Zones

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Abstract

The rapid growth of unmanned aerial vehicles (UAVs) has introduced new security challenges, particularly in restricted and high-security areas. Unauthorized drone intrusions pose threats such as espionage, smuggling, and disruption of critical infrastructure. This project proposes a smart surveillance system that detects and classifies unauthorized drones using deep learning. The system integrates the YOLOv5 object detection framework enhanced through transfer learning to distinguish drones from visually similar airborne objects, particularly birds. A curated drone–bird dataset was prepared for training, validation, and testing. The developed system achieves high real-time accuracy, robustness, and efficient aerial threat identification, making it suitable for deployment in sensitive environments. Experimental results demonstrate strong precision, recall, and mAP performance, confirming the effectiveness of the approach in improving situational awareness and countering unauthorized drone activities.

Keywords

Drone Detection, Deep Learning, YOLOv5, Transfer Learning, Surveillance System, Aerial Threat Identification

1. Introduction

Unmanned Aerial Vehicles (UAVs) have gained widespread adoption across various industries, including logistics, agriculture, monitoring, and imaging. Their accessibility and ease of operation, however, have raised concerns regarding unauthorized usage in restricted zones. Intrusions by unauthorized drones may lead to privacy violations, smuggling, security breaches, and disruptions of sensitive operations.

Traditional drone detection methods—such as radar, acoustic sensing, and RF scanning—struggle with small, low-altitude drones and fail to differentiate drones from natural objects like birds. Modern advancements in computer vision offer improved detection and classification capabilities.

This project presents a smart surveillance system employing YOLOv5 with transfer learning for real-time drone detection. A dedicated dataset of drone and bird images supports accurate differentiation to minimize false alarms. The system aims to enhance surveillance efficiency in high-security environments.

2. Literature Review

Early research employed radar systems, which offer long-range detection but suffer from low signatures of small drones. Acoustic detection using microphone arrays is prone to environmental noise, while RF analysis is limited to drones emitting identifiable communication signals.

Image-based approaches emerged with traditional machine learning, using handcrafted features such as edges and shapes. However, varying lighting and environmental conditions affected performance.

Deep learning revolutionized object detection through CNN-based frameworks like Faster R-CNN, SSD, and YOLO. YOLO's real-time capability made it widely preferred for surveillance tasks. Studies highlight the difficulty in distinguishing drones from birds, emphasizing dataset diversity and transfer learning.

YOLOv5, known for its lightweight architecture and improved accuracy, is increasingly used in drone detection due to its speed and performance.

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3. Problem Statement

Growing drone usage has increased unauthorized aerial intrusions into restricted zones. Traditional detection systems exhibit poor performance with small drones and lack reliable drone-bird differentiation. There is a need for an intelligent, real-time, accurate detection system that identifies unauthorized drones and alerts security personnel promptly. This project addresses this challenge using deep learning-based surveillance.

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4. Objectives

Primary Objectives

- Develop a smart surveillance system for detecting and classifying unauthorized drones.
- Implement YOLOv5 with transfer learning for accurate drone–bird differentiation.
- Enable real-time monitoring and threat identification.

Secondary Objectives

- Collect and preprocess a high-quality dataset of drone and bird images.
- Evaluate system performance using precision, recall, and mAP.
- Integrate the trained model into a live surveillance pipeline.
- Minimize false positives and enhance system reliability.

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5. Methodology

Phase 1: Data Collection & Preprocessing

A dataset of drone and bird images was sourced from publicly available collections. Tasks included:

- Image resizing and normalization
- Annotation in YOLO format
- Data augmentation (rotation, flipping, brightness adjustment, noise addition)

Phase 2: Model Selection

YOLOv5 was selected due to:

- High detection accuracy
- Fast inference speed
- Suitability for real-time deployment

Phase 3: Transfer Learning

A pre-trained YOLOv5 model was fine-tuned on the custom dataset. Key hyperparameters (learning rate, batch size, epochs) were optimized.

Phase 4: Model Training & Validation

The dataset was split into:

- 70% training
- 20% validation
- 10% testing

Performance was evaluated each epoch using standard detection metrics.

Phase 5: Real-Time Integration

The trained model was integrated into a live monitoring system capable of performing continuous detection and triggering alerts upon threats.

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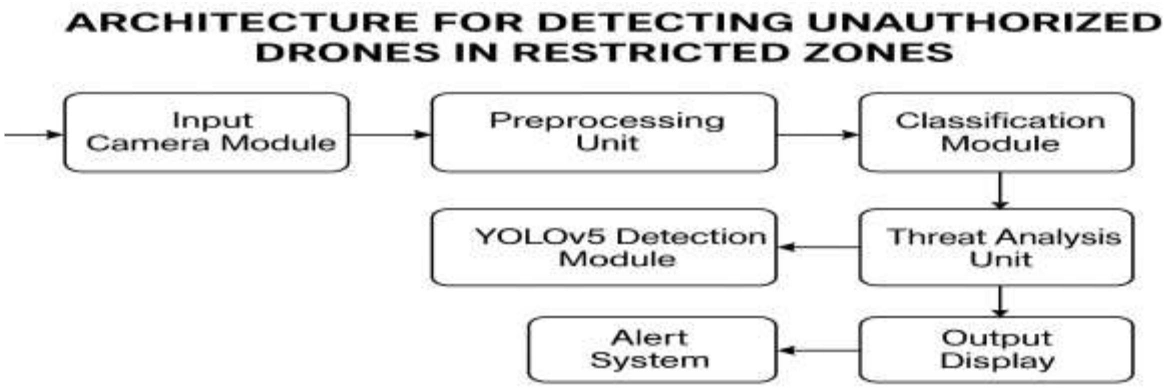
6. System Architecture

Components

1. **Input Camera Module** – Captures live video.
2. **Pre-processing Unit** – Resizes and normalizes frames.
3. **YOLOv5 Detection Module** – Performs object detection.
4. **Classification Module** – Distinguishes drones from birds.
5. **Threat Analysis Unit** – Checks if a detected drone is unauthorized.
6. **Alert System** – Sends alarms or notifications.
7. **Output Display** – Shows bounding boxes and detection results.

This architecture supports low-latency inference and efficient threat response. The architecture diagram as shown below:



7. Block Diagram Description

A detailed explanation of each stage:

1. Camera Feed Input

Live video is obtained using a static or PTZ camera, continuously monitoring the surveillance zone.

2. Frame Extraction

The video stream is broken into frames for analysis.

3. Preprocessing

Includes:

- Resizing
- Normalizing
- Converting color formats

Ensures consistency and noise reduction.

4. YOLOv5 Detection Engine

Performs:

- Object localization
- Bounding box prediction
- Confidence scoring

Fine-tuned via transfer learning for high-precision drone detection.

5. Classification

Objects are categorized as:

- Drone (potential threat)
- Bird (no threat)

6. Threat Assessment

Determines:

- Drone proximity
- Restricted zone violation
- Confidence level

7. Alert Generation

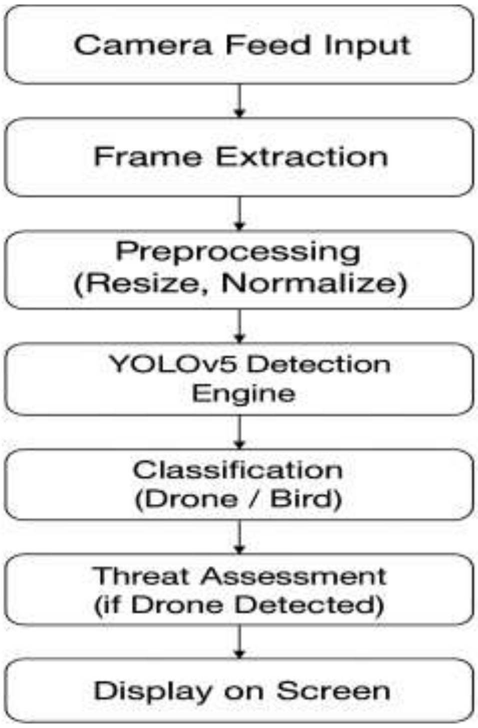
Triggers:

- Visual alerts
- Audio alarms
- SMS/Email notifications

8. Display on Screen

Outputs annotated frames with labels and confidence scores.

The system loops continuously for real-time surveillance. The block diagram as shown below:



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8. Dataset Description

- **Total Images:** ~3000–5000
- **Classes:** Drone, Bird
- **Annotations:** YOLO-compliant
- **Splits:**
  - Train: 70%

  - Validation: 20%
  - Test: 10%
- **Augmentations:** rotation, flip, brightness, noise

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9. Results and Discussion

- **Precision:** High accuracy in detecting relevant objects
- **Recall:** Strong performance across diverse environments
- **mAP:** ≈ 85–95%
- **Inference Speed:** 30–45 FPS (GPU)

The model distinguished drones from birds effectively, with minor performance drops under low-light conditions.

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10. Conclusion

A real-time smart surveillance system was successfully developed using YOLOv5 and transfer learning. The system achieved high detection accuracy and reliable classification, making it suitable for high-security deployments. Future improvements may include nighttime detection, thermal imaging, and embedded deployment.

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11. Applications

- Military bases
- Airports
- Defense facilities
- Border monitoring
- Critical infrastructure

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12. Limitations

- Degraded performance in low-light or fog
- Real-time detection requires GPU
- Dataset limitations may affect generalization
- Difficulty with high-speed or distant drones

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13. Future Enhancements

- Integration with thermal/IR cameras
- Flight trajectory prediction
- On-drone surveillance deployment
- Hybrid audio-visual detection
- Larger and more diverse dataset

14. References

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