Deep Learning-Based Drone Detection for Counter-UAV Cybersecurity Using YOLOv8

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***Abstract*—The rapid growth of unmanned aerial vehicles (UAVs) has created new opportunities in civilian, industrial, and commercial domains, but it has also introduced security risks in sensitive environments such as airports, military zones, critical infrastructure, and government facilities. Unauthorized drones may be used for illegal surveillance, smuggling, data interception, or cyber-physical attacks. For this reason, early and reliable drone detection has become an important layer in counter-UAV cybersecurity systems. This paper presents a vision-based drone detection system using the YOLOv8 object detection framework. The system is trained to identify two UAV categories, namely multirotor and fixed-wing drones, using a custom annotated image dataset. The proposed workflow includes dataset preparation, model training, performance evaluation, and deployment through image, video, real-time stream, and web-based detection interfaces. Experimental results show high precision, indicating that the model can identify detected UAVs with a relatively low false-positive rate. However, the recall value reveals that small and distant drones remain challenging. The study demonstrates the practical value of deep learning for counter-UAV cybersecurity while identifying future improvements related to dataset expansion, preprocessing, and small-object detection.**

***Index Terms*—Drone detection, UAV detection, counter-UAV cybersecurity, YOLOv8, deep learning, image processing, object detection, computer vision**

I. Introduction

Unmanned aerial vehicles (UAVs), commonly known as drones, have become widely available due to their decreasing cost, compact design, and growing range of civilian and commercial applications. Drones are now used in aerial photography, inspection, delivery, surveillance, search and rescue, agriculture, and environmental monitoring. While these applications are valuable, the same accessibility also creates serious security concerns. Unauthorized UAVs can enter restricted areas, collect sensitive visual information, support smuggling activities, or act as platforms for cyber-physical attacks.

In counter-UAV cybersecurity, detection is the first layer of defense. A security system cannot classify, track, jam, or neutralize a drone unless it first detects its presence with acceptable reliability. Several sensing technologies have been explored for this purpose, including radar, radio-frequency monitoring, acoustic sensing, thermal imaging, and visual camera systems. Among these, vision-based detection is especially attractive because it can operate passively, integrate with existing surveillance cameras, and provide visual evidence for human operators.

However, detecting drones in visual scenes is not a simple object-detection problem. UAVs often appear as small objects, especially when flying at high altitude or long distance. Their visual appearance may be confused with birds, clouds, aircraft, wires, or other background objects. Illumination changes, weather conditions, motion blur, and occlusions further increase the difficulty. These challenges have encouraged the use of deep learning models, particularly convolutional neural networks (CNNs) and YOLO-based one-stage detectors, for real-time UAV detection [2]–[4].

This project develops a YOLOv8-based vision system for drone detection in counter-UAV cybersecurity applications. The model is trained to detect and classify UAVs into two categories: multirotor drones and fixed-wing drones. The system supports detection from static images, recorded videos, live camera streams, and a web-based application. The main contribution of the project is an applied end-to-end detection pipeline that connects image dataset preparation, model training, evaluation, and practical deployment.

II. Related Work

A. Vision-Based Drone Detection in Counter-UAV Systems

Drone detection is a core component of counter-UAV systems because it provides the earliest warning of possible aerial intrusion. Radar and radio-frequency approaches can be useful, but they may require specialized hardware and may be affected by environmental or operational constraints. Vision-based systems offer an alternative that can reuse camera infrastructure and provide interpretable visual outputs. For this reason, image processing and deep learning have become important tools in counter-UAV research [1], [2].

The main difficulty in visual UAV detection is that drones are often small, fast, and visually weak compared with their background. A drone may occupy only a few pixels in a frame, especially in long-range surveillance. In addition, the system must distinguish UAVs from visually similar aerial objects. These conditions make simple thresholding or shape-based detection insufficient in many real-world cases.

B. Classical Image Processing Approaches

Early vision-based drone detection systems relied heavily on classical image processing methods such as grayscale conversion, histogram equalization, background subtraction, motion detection, contour extraction, and handcrafted feature descriptors. Hamatapa and Vongchumyen proposed an image processing approach for drone detection that used visual pre-processing and feature-based detection in controlled scenarios [1]. Such methods are computationally efficient and can be useful in low-cost surveillance systems.

Despite their efficiency, classical methods often depend strongly on stable backgrounds, good illumination, and clear object boundaries. In counter-UAV cybersecurity, these assumptions are not always realistic. Drones may fly against cluttered skies, near buildings, or under low-light conditions. As a result, classical image processing alone usually lacks the robustness required for reliable security deployment.

C. Deep Learning-Based Drone Detection

Deep learning has improved object detection by allowing models to learn discriminative visual features directly from data. YOLO-based detectors are especially suitable for real-time applications because they treat object detection as a single-stage prediction problem. Instead of using a separate region-proposal stage, YOLO models predict bounding boxes and class probabilities efficiently in one forward pass.

Dewangan et al. studied the use of image processing techniques with deep learning for UAV detection and reported that preprocessing can improve detection under difficult visual conditions, especially when UAVs are small or distant [2]. Garvanov et al. also emphasized that small flying objects remain difficult for visual detection systems and that image-processing support can improve recognition reliability [3]. In addition, real-time flying object detection studies using YOLOv8 show that the model can provide a useful balance between accuracy and inference speed for airborne object detection [4].

YOLOv8, maintained by Ultralytics, supports object detection and related computer vision tasks through a unified training and deployment framework [5]. Its lightweight variants, such as YOLOv8n, are useful when real-time speed and limited computational resources are important. For counter-UAV cybersecurity, this is valuable because detection systems may need to operate continuously on edge devices or surveillance workstations.

D. Research Gap

The reviewed literature shows that classical image processing is efficient but sensitive to environmental variability, while deep learning offers better adaptability but still struggles with small and distant UAVs. Therefore, a practical research gap remains in building robust and deployable drone detection pipelines that combine data preparation, model training, evaluation, and real-world use. This project addresses that gap at an applied level by implementing and evaluating a YOLOv8-based UAV detection system for counter-UAV cybersecurity.

III. Proposed Method

A. System Overview

The proposed system follows an end-to-end object detection pipeline. Input data can be a static image, recorded video, or live camera stream. Each frame is passed to the trained YOLOv8 model, which returns bounding boxes, class labels, and confidence scores. The output is then visualized by drawing bounding boxes around detected drones and labeling each detection as either multirotor or fixed-wing.

The workflow consists of five main stages: dataset preparation, annotation formatting, model training, evaluation, and deployment. This structure allows the system to move from raw image data to a usable application interface rather than remaining only a training experiment.

B. Dataset Preparation

The dataset used in this project contains approximately 1,360 annotated UAV images. It includes two classes: multirotor drones and fixed-wing drones. Images were collected from publicly available online sources and curated to include variation in object size, background, viewing angle, and illumination. This diversity is important because UAVs may appear differently depending on distance, camera angle, drone type, and environmental conditions.

All images were annotated using the YOLO format. In this format, each object is represented by a class identifier and normalized bounding box coordinates. The normalized coordinates allow the same annotation structure to remain valid across image resizing operations during training. The dataset was organized into training and validation subsets to support model development and performance evaluation.

C. Model Architecture

The system uses YOLOv8n as the core detection model. YOLOv8n is the nano variant of YOLOv8, designed for fast inference with a relatively small computational footprint. This makes it suitable for real-time or near-real-time detection tasks where latency matters. YOLOv8 uses a CNN-based architecture composed of a backbone for feature extraction, a neck for multi-scale feature fusion, and a detection head for bounding box regression and class prediction [5], [6].

For UAV detection, multi-scale feature representation is important because drones may appear at different sizes in the same scene. A drone close to the camera can occupy a large region, while a distant drone may appear as a tiny object. The model must therefore learn both fine local details and broader contextual features.

D. Training Configuration

Model training was performed using the Ultralytics YOLOv8 framework. The model was trained for 51 epochs with an input resolution of 640×640 pixels and a batch size of 32. Mixed precision training was enabled to improve training efficiency and reduce memory usage when supported by the hardware.

The training environment automatically selected the available computing device, such as a CUDA-enabled GPU, Apple Silicon MPS, or CPU. During training, checkpoints were saved and the best model was selected according to validation performance. This configuration aimed to balance speed, stability, and practical deployability.

IV. Deployment and Application

After training, the YOLOv8 model was deployed for practical drone detection. The system supports three main detection modes. First, it can process static images and return annotated images with bounding boxes. Second, it can process recorded video files frame by frame. Third, it can run on real-time video streams, making it useful for surveillance-style scenarios.

A web-based interface was also developed using Streamlit. The web application allows users to upload images and receive detection outputs with class labels and per-class counts. This interface improves usability because it allows non-specialist users to test the system without directly running Python scripts or command-line tools. The deployed application is available online, and the project source code is hosted in a public GitHub repository.

V. Experimental Results

The trained model was evaluated using common object detection metrics, including precision, recall, mean average precision at an IoU threshold of 0.5 (mAP@0.5), and mean average precision across IoU thresholds from 0.5 to 0.95 (mAP@0.5:0.95). These metrics provide different views of detection quality. Precision measures the proportion of predicted detections that are correct, while recall measures the proportion of actual objects that are successfully detected. Mean average precision evaluates both classification and localization quality across confidence thresholds.

The model achieved a precision of 89.4%, which indicates that most predicted drone detections were correct. This is important in security environments because excessive false positives can cause unnecessary alerts and reduce operator trust. However, the recall value was 17.3%, showing that many UAV instances were missed. This result reflects one of the main difficulties of drone detection: small and distant UAVs may be hard to identify, even for modern deep learning models.

The system achieved an mAP@0.5 of 30.0% and an mAP@0.5:0.95 of 23.5%. These values indicate moderate overall detection performance. The gap between precision and recall suggests that the model is conservative: when it detects a drone, the detection is often correct, but it does not detect all drones present in the data.

Training loss values decreased consistently during the training process. The bounding box regression loss decreased from 1.48 to 0.94, the classification loss decreased from 1.33 to 0.53, and the distribution focal loss decreased from 1.80 to 1.36. This trend indicates that the model learned meaningful patterns from the training data and that the training process converged in a stable manner.

TABLE I
Detection Performance of the YOLOv8-Based UAV Detection Model

Metric	Value
Precision	89.4%
Recall	17.3%
mAP@0.5	30.0%
mAP@0.5:0.95	23.5%

TABLE II
Training Loss Reduction

Loss Type	Initial Value	Final Value
Bounding box loss	1.48	0.94
Classification loss	1.33	0.53
Distribution focal loss	1.80	1.36

Qualitative testing also showed that the system can detect and classify UAVs in images, videos, and real-time streams. The web application provides annotated outputs and counts for uploaded images, making the system more practical for demonstration and user interaction.

VI. Discussion

The results show that the proposed YOLOv8-based system is promising for drone detection in counter-UAV cybersecurity, particularly when the goal is to reduce false alarms. The high precision value suggests that the model is careful in assigning the UAV label and can provide useful detections in security-sensitive contexts. This is valuable because false alarms may trigger unnecessary investigation, operator fatigue, or operational interruption.

At the same time, the low recall value reveals an important limitation. In counter-UAV cybersecurity, missing a drone may be more dangerous than producing a false alarm, especially in restricted airspace. The recall result suggests that the model requires further improvement before it can be considered reliable as a standalone operational detector. This limitation is consistent with previous studies showing that small object detection remains a major challenge in UAV detection [2], [3], [7].

Several factors may explain the recall limitation. First, the dataset size is relatively small for a deep learning object detector. Second, distant UAVs may occupy very few pixels, making visual features weak. Third, class imbalance or limited environmental diversity may reduce generalization. Finally, the lightweight YOLOv8n model prioritizes speed, but larger model variants may provide better feature extraction and higher detection sensitivity.

Compared with classical image processing methods, the proposed deep learning approach is more adaptable to different backgrounds and drone shapes. However, classical preprocessing techniques may still be useful as support layers. For example, contrast enhancement, super-resolution, motion-based region proposal, or thermal-image fusion could improve the visibility of small drones before detection. Therefore, future improvements should not treat image processing and deep learning as separate choices, but as complementary components.

VII. Conclusion and Future Work

This paper presented a YOLOv8-based drone detection system for counter-UAV cybersecurity applications. The system detects and classifies UAVs into multirotor and fixed-wing categories and supports image, video, real-time stream, and web-based detection. The results show that the model achieves high precision, making it useful for scenarios where false positives should be minimized. However, the low recall value highlights the continuing difficulty of detecting small and distant UAVs.

Future work should focus on improving detection sensitivity while preserving precision. The most direct improvement is to expand the dataset with more diverse scenes, drone scales, weather conditions, camera viewpoints, and background types. Advanced augmentation strategies, larger YOLOv8 variants, small-object detection modules, and image preprocessing techniques may also improve recall. Another important direction is to evaluate the model on independent real-world video sequences and measure inference speed on deployment hardware.

Overall, the project demonstrates that deep learning and image processing can contribute to counter-UAV cybersecurity by providing an automated visual detection layer. While additional development is required for high-risk operational deployment, the proposed system provides a practical foundation for UAV detection research and application.

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