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Optimizing UAV Detection Performance with YOLOv5 Series Algorithms

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ABSTRACT
This paper provides a comprehensive evaluation of the YOLOv5 series, including YOLOv5n, YOLOv5s, YOLOv5m, and YOLOv5l, with a specific focus on their effectiveness in drone detection applications. By analyzing key performance metrics such as precision, recall, mAP50, mAP90, and F1-score, the study identifies YOLOv5s as the standout performer, achieving the highest precision (98.75%) and mAP50 (97.8%). These results highlight its exceptional object detection capabilities. The study also examines inference speed and computational requirements, revealing the trade-offs between accuracy and computational efficiency when selecting YOLOv5 models for drone detection tasks. Despite these trade-offs, YOLOv5s proves to be a promising candidate, offering a well-balanced combination of precision, recall, and computational efficiency. This balance makes YOLOv5s particularly well-suited for practical deployment in real-world drone detection systems, where both accuracy and operational efficiency are critical. Overall, the findings of this study provide valuable insights for researchers and practitioners aiming to optimize drone detection capabilities using YOLOv5 models.

KEYWORDS
UAV Detection, Drone Detection, YOLOv5, Deep Learning, Object Detection, Autonomous Drone, Computer Vison

1. INTRODUCTION

According to data released by the Federal Aviation Administration (FAA) on December 31, 2023, there are 790,918 registered drones in the United States. This total includes 369,528 commercial drones, 416,095 recreational drones, and 5,295 paper drones[1]. Drones have advanced capabilities such as autonomous landing and takeoff, environmental adaptation, high-altitude flight, and stationary hovering. However, as drone usage increases, so do safety concerns. The drone industry is rapidly expanding and becoming more accessible to the public due to decreasing costs. Depending on their payload capacity, drones are used for a variety of purposes, including inspection[2], delivery[3], agriculture[4], healthcare[5], high-voltage power line inspection[6], and search and rescue[7].

The rise in the number of drones increases the risk of malfunctions and failures, which can pose significant dangers. Additionally, drones can be used maliciously to carry explosives and target prominent buildings or government offices. Terrorist groups and illegal drug traffickers have also exploited drones for their activities[8]. Recreational drone users might inadvertently interfere with crucial operations such as firefighting and emergency response, exacerbating safety concerns[9].

To effectively develop a drone detection system, it is crucial to consider the various threats posed by unmanned aerial vehicles (UAVs). The main categories of these threats include drone attacks, illicit smuggling, drone espionage, and drone collisions. An illustrative case study is provided below:

On August 13, 2023, in Absecon, New Jersey, USA, allegations arose that the owner of a heating and air conditioning company used a drone to disperse harmful chemicals into a commercial establishment as part of an attack[10]. Similarly, on June 3, 2022, authorities apprehended a 55-year-old individual for utilizing his drone to release illegal fireworks [11]. Drones have been used previously in attacks on Venice, Italy, using unmanned balloons loaded with explosives[12]. Thirteen small drones attacked Russian forces in Syria in more recent incidents, suffering serious harm[13]. On February 22, 2024, Indian Border Security Force (BSF) troops discovered an improvised explosive device dropped by a drone in a village near the international border, close to Kathua district in Jammu, India[14]. On January 17, 2024, an unauthorized drone captured footage of Taloja Jail [15].

Ensuring the safe and proper use of drones is critical, necessitating timely and precise detection methods. However, spotting drones can be difficult due to their small size and resemblance to planes or birds. Effective drone detection employs various sensor technologies to identify the presence, location, or distinctive features of drones. These sensor systems can detect different signals emitted by drones, such as sound waves, Doppler effects, RF signals, and heat signatures. By analyzing these signals, drones can be identified within a specific area.

Drone detection systems are typically categorized into four types based on the sensing technology used: Acoustic detection, RF detection, Radar detection, and Visual detection. Traditional radar systems often struggle to detect small drones due to their minimal electromagnetic signal emissions. Although acoustic and radio frequency detection methods are effective, they can be expensive and face challenges, such as addressing the Doppler effect adequately. In contrast, deep learning-based object detection has gained traction due to its high accuracy and the availability of powerful computing resources.

Deep learning is a powerful technique that has shown great promise in fields like computer vision and pattern recognition. Object detection methods using deep learning typically fall into two categories: two-stage and one-stage approaches.

Two-Stage Detectors: Two-stage detectors, such as the R-CNN series, begin by generating region proposals using methods like selective search. These proposals are then processed for feature extraction and refinement via a Convolutional Neural Network (CNN), followed by classification and bounding box determination. To streamline these computations, advancements such as Fast R-CNN, Faster R-CNN, and Mask R-CNN have been introduced.

One-Stage Detectors: In contrast, one-stage approaches like Single Shot MultiBox Detector (SSD) and You Only Look Once (YOLO) compute the entire image directly to produce detection results. While one-stage methods offer faster detection speeds, they may sacrifice some accuracy compared to the more precise, albeit slower, two-stage methods.

A significant advancement in the YOLO series, YOLOv5, demonstrates remarkable progress in real-time object detection, excelling in both accuracy and speed. Utilizing cutting-edge backbone and neck architectures, YOLOv5 significantly enhances feature extraction and object detection functionalities. Its innovative anchor-free split Ultralytics head not only improves accuracy but also enhances efficiency compared to traditional anchor-based methods. Prioritizing an optimized balance between accuracy and speed, YOLOv5 proves highly proficient for real-time object detection across various applications. Additionally, it offers a range of pre-trained models tailored to different tasks and performance requirements, ensuring user-friendly flexibility and ease of implementation.

The primary contributions of this paper include:

- Analyzing the YOLOv5 series of object identification algorithms, which comprises variants such as YOLOv5s, YOLOv5m, YOLOv5n, and YOLOv5l.

- Tracking performance metrics such as mean average precision (mAP), recall (R), precision, and F1-Score, provides essential insights into the effectiveness of these algorithms.

The paper is structured as follows:

Section 2 outlines our approach to drone detection using YOLO. Section 3 offers a detailed overview of the proposed system, covering its architecture, hardware components, software infrastructure, Graphical User Interface (GUI), and dataset. Section 4 presents and analyses the experimental results derived from the study. Section 5 discusses the findings, presents conclusions, and outlines future research directions.

2. Drone Detection Methodology Using YOLOv5 Algorithm

The YOLOv5 model, an earlier advancement in the YOLO series, has made significant strides in object detection, image classification, and instance segmentation. This paper focuses on its application in drone detection. YOLOv5 features a streamlined architecture designed to optimize both speed and accuracy. It employs a CSPDarknet backbone, which enhances feature extraction by partitioning the feature map of the base layer and then merging it through a cross-stage hierarchy. This structure improves gradient flow and reduces computational cost.

YOLOv5 uses a combination of anchor-based detection and a decoupled head, which splits the detection task into classification and localization branches. This decoupling allows each branch to focus on its specific task, thereby enhancing overall performance. Additionally, YOLOv5 integrates a variety of data augmentation techniques, such as mosaic augmentation and adaptive image scaling, to improve the model’s robustness and generalization capabilities.

At the output layer, YOLOv5 employs the sigmoid function for objectness scores and the SoftMax function for class probabilities, ensuring precise and confident predictions. These design choices contribute to YOLOv5’s superior detection accuracy and efficiency, making it a powerful tool for real-time object detection tasks, including drone detection.

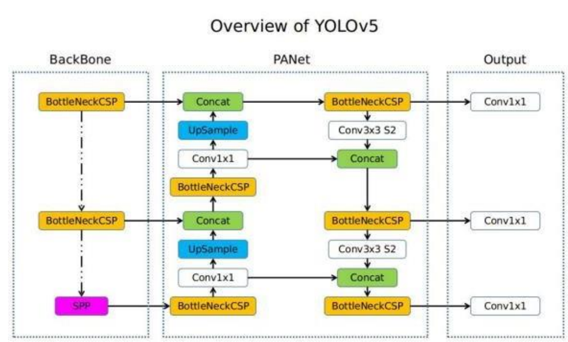

Fig. 1 Architecture of YOLOv5[23]

3. Experimental Setup

For our drone detection project, we curated a dataset from various public platforms such as Kaggle and Google, ensuring a diverse collection of images taken from different altitudes, angles, backgrounds, and perspectives. Additionally, we captured some images during our own flights. The dataset comprised 4,614 images depicting various types of drones. To train and evaluate our YOLOv5 Series model, we split the dataset into 80% for training (3,691 images) and 20% for testing (923 images).

Our experimental setup utilized a Nvidia RTX 2060 GPU accelerator and an Intel i7-10800 CPU with eight-core processors, supported by 32GB of DDR4-3200 RAM. The runtime environment included 64-bit Ubuntu configured with CUDA 12.1, PyTorch 2.1.8, and Python 3.11.6. Figure 2 illustrates an augmented dataset.

Fig. 2 Augmented Dataset

4. RESULTS AND PERFORMANCE EVALUATION

4.1 Evaluation Metrics

To ensure the efficacy of a real-time drone detection model, it is essential to evaluate its performance based on specific criteria. Frames per second (FPS) and Mean Average Precision (mAP) are key indicators for determining the optimal model for drone identification. FPS measures the detection speed, while mAP quantifies accuracy in detection. Precision and recall metrics are used to calculate mAP. Precision measures the accuracy of the model in identifying relevant objects by calculating the percentage of correct positive predictions. Recall assesses the model's effectiveness in detecting all relevant instances or ground-truth bounding boxes, expressed as the percentage of accurate positive predictions among all provided ground truths. To compute precision and recall, each detected bounding box must first be classified. These metrics are derived using specific equations.

$$Precision(P) = \frac{\sum T_P}{\sum T_P + F_P} \quad (1)$$

$$Recall\ (R) = \frac{\sum T_P}{\sum T_P + F_N} \quad (2)$$

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_n \quad (3)$$

$$F_1Score = \frac{2*(P*R)}{P+R} \quad (4)$$

Were,

T_P refers to True Positives,

T_N stands for True Negatives,

F_P represents False Positives, and

F_N indicates False Negatives.

4.2 Results

The YOLOv5 series underwent rigorous training sessions spanning 100 epochs, utilizing a dataset of 4614 images, including training, validation, and testing sets. Training durations varied, with the longest session exceeding 20 hours and the shortest taking less than 90 minutes. The efficacy of the trained YOLOv5 models was evaluated using comprehensive metrics such as F1-score, mean Average Precision (mAP), precision, and recall. Additionally, we examined the detection speed in videos, measured in frames per second (FPS). Our evaluation process included assessing mAP, precision, recall, and F1 scores, with FPS serving as a benchmark for video detection speed. Table 1 encapsulates the mAP, precision, recall, and F1 scores, reflecting the performance of various YOLOv5 variants on a testing dataset derived from a randomized train split. Moreover, Figure 3 visually compares the performance of YOLOv5 variants across precision, recall, and F1 score metrics.

Table 1: Training Performance of Yolov8 series.

Yolo Model	Precision	Recall	mAP50	mAP90	F1- Score
YOLOv5n	0.9559	0.9295	0.96147	0.60816	0.9425
YOLOv5s	0.9874	0.9507	0.9785	0.62475	0.9687
YOLOv5m	0.941	0.944	0.963	0.614	0.9424
YOLOv5l	0.957	0.947	0.974	0.68	0.9519

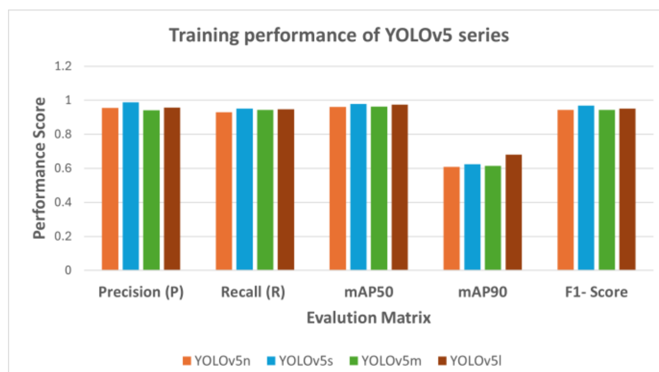

Fig. 3 Graphical Representation of Precision, Recall, and F1 Score and Accuracy of Yolov8 variant.

Figure 4: Real-time drone detection using YOLOv8

Variant.

5. Discussion and Conclusion

YOLOv5s demonstrates the best balance of precision, recall, and mAP for drone detection, offering a high level of accuracy while maintaining efficient computational demands. YOLOv5n provides the fastest inference times due to its high FPS, making it ideal for real-time applications where speed is critical. On the other hand, YOLOv5l offers high precision and recall but at the expense of lower FPS and longer training times, making it more suitable for non-real-time applications. Researchers should select the appropriate YOLOv5 variant based on the specific accuracy, speed, and resource constraints of their application.

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