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Comparative Analysis of YOLOv5, YOLOv4, and SSD for Aircraft Detection in Airport Environments Using Remote Sensing Data

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Abstract – Accurate and efficient detection of aircraft at airports is crucial for enhancing airport security, ensuring safe operations, and improving overall air traffic management. As airports grow in complexity and traffic density increases, automated object detection systems powered by advanced algorithms have become essential to support real-time monitoring and decision-making processes. This study presents a comprehensive evaluation of the YOLOv5 object detection algorithm for identifying aircraft at airports, comparing its performance against YOLOv4 and SSD. The goal was to determine the most effective algorithm for real-time detection in complex airport environments. YOLOv5 was trained and tested on a dataset of annotated images of aircraft, and its performance was assessed using precision, recall, mean average precision (mAP), F1 score, and inference speed as key metrics. Results show that YOLOv5 outperforms both YOLOv4 and SSD, achieving the highest precision (0.759), recall (0.772), mAP (0.766), and F1 score (0.765), while maintaining a competitive inference speed of 54 ms. In comparison, SSD demonstrated faster inference speed at 48 ms but lower detection accuracy, while YOLOv4 exhibited the lowest performance across all metrics. These findings indicate that YOLOv5 is the most suitable algorithm for real-time aircraft detection at airports, balancing high detection accuracy with efficient processing speed. This makes it a valuable tool for applications such as airport security and aerial monitoring.

Keywords – aircraft detection, airport security, aerlail monitoring, YOLO, SSD

I. Introduction

Object detection is a widely recognized technique in computer vision, attracting significant attention and undergoing extensive research. Its primary objective is to classify and locate objects within target images [1]. With the continuous advancement of deep learning algorithms over the years, sophisticated methods for object detection have emerged [2]. These technological developments have paved the way for groundbreaking innovations in artificial intelligence and image processing. Particularly since the early 2010s, the evolution and widespread adoption of Graphics Processing Unit (GPU) technologies have accelerated the processing of large datasets and the training of complex artificial intelligence models [3]. As a result, deep learning algorithms employed in challenging tasks like object detection have become more accurate, efficient, and robust. Convolutional Neural Networks (CNN)-based approaches, in particular, have revolutionized various industries by detecting intricate patterns in image data [4]. In the context of aviation, where airplanes are crucial for both transportation and military purposes, the application of deep learning algorithms for identifying and tracking aircraft locations is especially significant [5]. In civil aviation, precise and rapid aircraft detection plays a vital role in enhancing operational efficiency and ensuring safety, particularly in international airports with high air traffic volumes [6]. Monitoring aircraft movements within airports is essential for preventing potential traffic congestion on taxiways, runways, parking areas, and hangars [7]. In military operations, the continuous monitoring and real-time tracking of aircraft, especially those that pose a potential threat, are of strategic importance [8]. The rapid analysis capabilities enabled by deep learning algorithms enhance the effectiveness of air defense systems, making them more responsive and agile [9].

Machine learning-based solutions are poised to offer substantial improvements to object detection challenges [10]. Specifically, recent advancements in deep learning have revolutionized classification processes within object detection [11]. Today's object detection algorithms are broadly categorized into two main types: two-stage and single-stage approaches [12]. Two-stage algorithms, such as Region Convolutional Neural Networks (R-CNN) and their derivatives, are known for their high accuracy [13]. However, they are slower in terms of processing speed compared to single-stage models. Two-stage methods first identify potential object regions in an image, followed by classifying objects in these regions to make the final decision [14]. In contrast, single-stage algorithms, such as SSD and YOLO, excel in real-time detection by offering faster processing speeds [15]. These algorithms determine the locations and classifications of objects in a single pass through convolutional neural networks, providing superior computational efficiency and overall performance compared to other machine learning methods. In recent years, unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) have emerged as powerful tools in monitoring and data collection, particularly in applications requiring real-time surveillance and precision [16, 17]. UAVs offer significant advantages over traditional data collection methods due to their flexibility, ability to cover large areas quickly, and capacity to capture high-resolution imagery. These aerial platforms have become integral in fields such as disaster management, agriculture, environmental monitoring, and infrastructure inspection. In the context of object detection, UAVs play a crucial role in capturing valuable data from various perspectives and altitudes, enabling more comprehensive analyses. Their ability to operate in hard-to-reach or hazardous areas without risking human safety makes them particularly suitable for military surveillance, traffic monitoring, and search-and-rescue missions [18]. The real-time data collection capabilities of UAVs, combined with advancements in machine learning, have expanded their application scope in smart cities, transportation systems, and even remote sensing operations.

Remote sensing offers a unique advantage by providing high-resolution imagery across large geographical areas, making it ideal for applications that require extensive coverage, such as monitoring airports or large infrastructure sites. Satellite imagery, known for its global reach and consistent data collection capabilities, allows for continuous observation over extended periods. This is particularly useful for tracking large-scale changes or conducting regular surveillance. Meanwhile, UAVs complement satellite data by offering greater flexibility in terms of altitude, angle, and resolution. UAVs can capture real-time, detailed images from lower altitudes, making them suitable for tasks that require closer inspection or more immediate data acquisition. By combining satellite-based imagery with UAV-based data, this study achieves a more comprehensive analysis, leveraging the strengths of both platforms to enhance the accuracy and effectiveness of the object detection process.

In this study, the YOLOv5 algorithm was trained on a comprehensive dataset of aircraft images collected from both satellite and UAV sources, which were annotated to accurately reflect the diverse conditions and angles typically found in airport environments. The performance of YOLOv5 was then rigorously evaluated using key metrics, including precision, recall, mean average precision (mAP), F1 score, and inference speed, to assess its detection capabilities. For comparative purposes, the same tests were also conducted using the YOLOv4 and SSD algorithms. The results were compiled and analyzed to determine which model was most effective for real-time aircraft detection. The findings are presented in detail, highlighting the strengths and weaknesses of each algorithm, with particular emphasis on YOLOv5's superior accuracy and suitability for real-time applications. Additionally, the study discusses the potential of integrating these detection models into airport monitoring systems, providing insights into their operational efficiency and practical applications.

II. Materials and Method

A. YOLO Algorithm

The YOLO algorithm is a highly efficient and fast method for object detection in image processing [19]. Unlike traditional object detection algorithms, which typically scan the entire image and generate object bounding boxes one by one, YOLO divides the input image into a grid system, speeding up the detection process significantly. Each grid cell is responsible for detecting objects whose center falls within that cell, and bounding boxes are predicted for these objects. Additionally, each box is assigned a prediction vector, including the object's class and the confidence score, which indicates both the presence of an object in a particular grid cell and the detection accuracy [20]. The YOLOv5 algorithm, a PyTorch-based model, stands out for being lighter and faster compared to its predecessors, YOLOv3 and YOLOv4. Its open-source nature has made it a popular choice among researchers and developers, as it allows for greater flexibility in customization. YOLOv5, introduced by Ultralytics in 2020, is an advanced version of the YOLO object detection models [21]. Unlike its predecessors, which were developed on the Darknet framework, YOLOv5 is based on the PyTorch library, which offers easier adaptability and customization for developers [22]. YOLOv5, whose architecture is shown in Fig. 1, comes in four variants, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, each optimized for different trade-offs between speed and accuracy. Despite differences in complexity and model size, all versions maintain a balance between detection performance and inference speed, making them suitable for a variety of applications [23].

The YOLOv5 architecture is composed of four main components: Input, Backbone, Neck, and Head. The backbone network is responsible for extracting features from the input image. It consists of several layers, including Conv_LR, BottleNeckCSP, and Spatial Pyramid Pooling (SPP) modules. The Conv_LR layers focus on extracting low-level features from the image and use various filters to enhance diversity. The BottleNeckCSP module reduces computational complexity and enables more efficient parameter usage, which is particularly useful for large datasets. The SPP module enriches feature maps by aggregating information at different scales, enabling the model to detect objects of varying sizes more effectively. The Neck component bridges the gap between the Backbone and Head, using Path Aggregation Network (PANet) and Feature Pyramid Network (FPN) modules. PANet aggregates higher-level features, helping the network detect smaller and low-resolution objects with greater accuracy. FPN, on the other hand, enhances feature maps by combining low-level and high-level information. The integration of PANet and FPN enables multi-scale feature fusion, leading to more robust object detection across different resolutions. The Head is where the final object detection and classification occur. Using the features extracted and processed by the Backbone and Neck, the Head predicts the bounding boxes and classifies objects in the image.

B. Loss Function

In YOLOv5, the loss function is a critical component for optimizing the model during training. The loss function used in YOLOv5 is composed of three primary components: bounding box loss, objectness loss, and classification loss. The bounding box loss calculates the difference between the predicted and actual locations of objects. This is typically computed using a variant of the Intersection over Union (IoU) metric, which measures the overlap between the predicted bounding box and the ground truth. Objectness loss measures the model's confidence that an object exists within a predicted box. Finally, classification loss calculates the error in predicting the correct class label for each detected object. These components are weighted and combined into a single

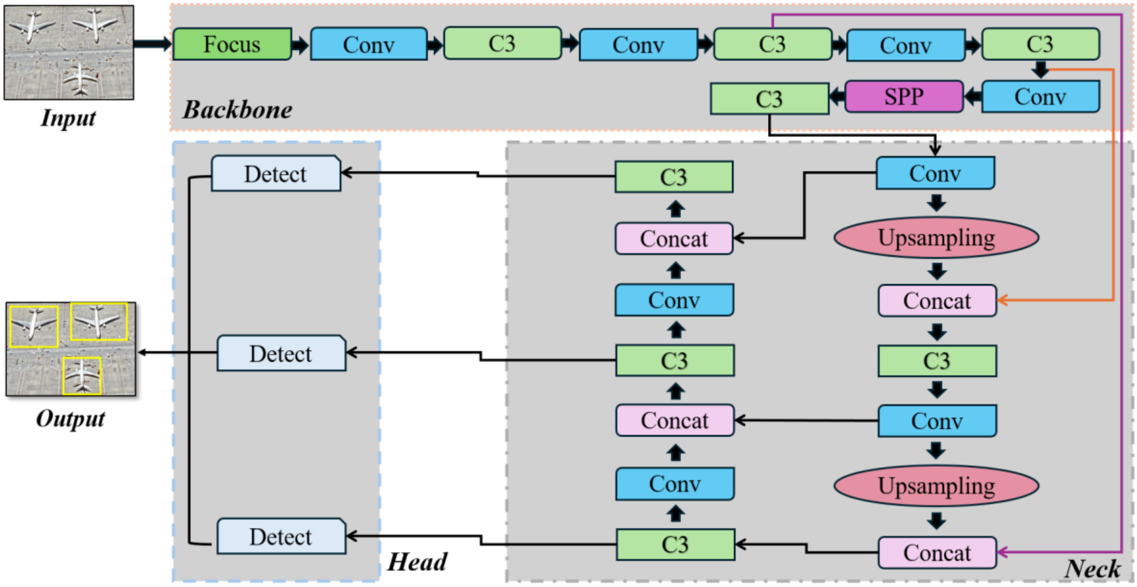

Fig. 1. Network architecture of YOLOv5 model.

loss function, which is minimized during training to improve the accuracy and precision of the model's predictions.

C. Dataset

The dataset used for training and evaluating YOLOv5 in this study comprises a combination of satellite and UAV images, with the primary focus on detecting aircraft on the ground. The images were sourced from high-resolution satellite imagery and UAV-based aerial photography to provide comprehensive coverage and varying perspectives of airport environments. The dataset was carefully curated and annotated to ensure accurate labeling of aircraft, capturing various conditions such as different lighting, angles, and aircraft positions. The dataset contains 5377 images with a diverse set of scenes, ensuring that the model is trained to recognize aircraft under a wide range of conditions. Additionally, the dataset was augmented with techniques such as flipping, rotation, and color adjustments to increase variability and improve the model's robustness.

D. Network Training

Training the YOLOv5 model involved multiple stages, beginning with pre-processing the dataset. The images were resized (480x480 pixels) to fit the input requirements of the YOLOv5 network. During training, the model was initialized with pre-trained weights from the COCO dataset to accelerate convergence and improve performance. The Adam optimizer was used to adjust the model's weights based on the calculated loss function, and a learning rate scheduler was employed to dynamically adjust the learning rate during training to avoid overfitting and achieve optimal performance. The training process was carried out using Google Colab, utilizing its GPU resources to speed up computations. The model was trained for 200 epochs, and early stopping was applied to prevent overfitting. In addition, data augmentation was applied during training to enhance the model's ability to generalize to new data.

III. Results

The detection process began by training the YOLOv5 on the prepared dataset, which consisted of annotated images of aircraft at airports captured from various angles and under different lighting conditions. The dataset was carefully pre-processed to ensure optimal training, with a focus on balancing classes and maintaining high-quality annotations. During the training phase, the algorithm was exposed to a large volume of labeled images, allowing it to learn to recognize aircraft at varying scales and positions within complex airport environments. After completing the training, the algorithm's performance was validated using a separate validation dataset that had not been seen during training. This validation step was crucial in assessing the generalization capability of YOLOv5 and ensuring it did not overfit the training data, providing a reliable indication of its real-world detection performance. Once the training and validation phases were completed, the algorithm was tested on a set of unseed images that were not included in the original training or validation datasets. These tests aimed to evaluate the model's ability to accurately detect aircraft in unseen scenarios, further demonstrating the robustness of YOLOv5 in real-world applications. The model consistently identified aircraft with high accuracy, successfully detecting planes in various positions and orientations within the airport environment. Examples of detection results are presented in Fig. 2, where bounding boxes highlight the locations of aircraft detected by YOLOv5. The figure showcases the model's ability to accurately identify aircraft amidst complex airport structures and backgrounds, reinforcing the effectiveness of the detection system.

Table 1 presents a detailed comparison of the performance metrics, precision, recall, mean average precision (mAP), F1 score, and inference speed, for the three object detection algorithms: YOLOv5, YOLOv4, and SSD [24]. These metrics collectively provide insights into the strengths and weaknesses of each algorithm for detecting aircraft in airport environments. Starting with precision, YOLOv5 demonstrates superior performance with a value of 0.759, indicating that the algorithm has fewer false positives compared to the other models. YOLOv5's high precision means that when the algorithm identifies an object as an aircraft, it is more likely to be correct. In contrast, YOLOv4 and SSD lag behind, with precision values of 0.671 and 0.715, respectively. SSD performs better than YOLOv4 in precision, possibly due to its different architecture, which is designed to handle smaller objects and densely populated scenes. However, neither of

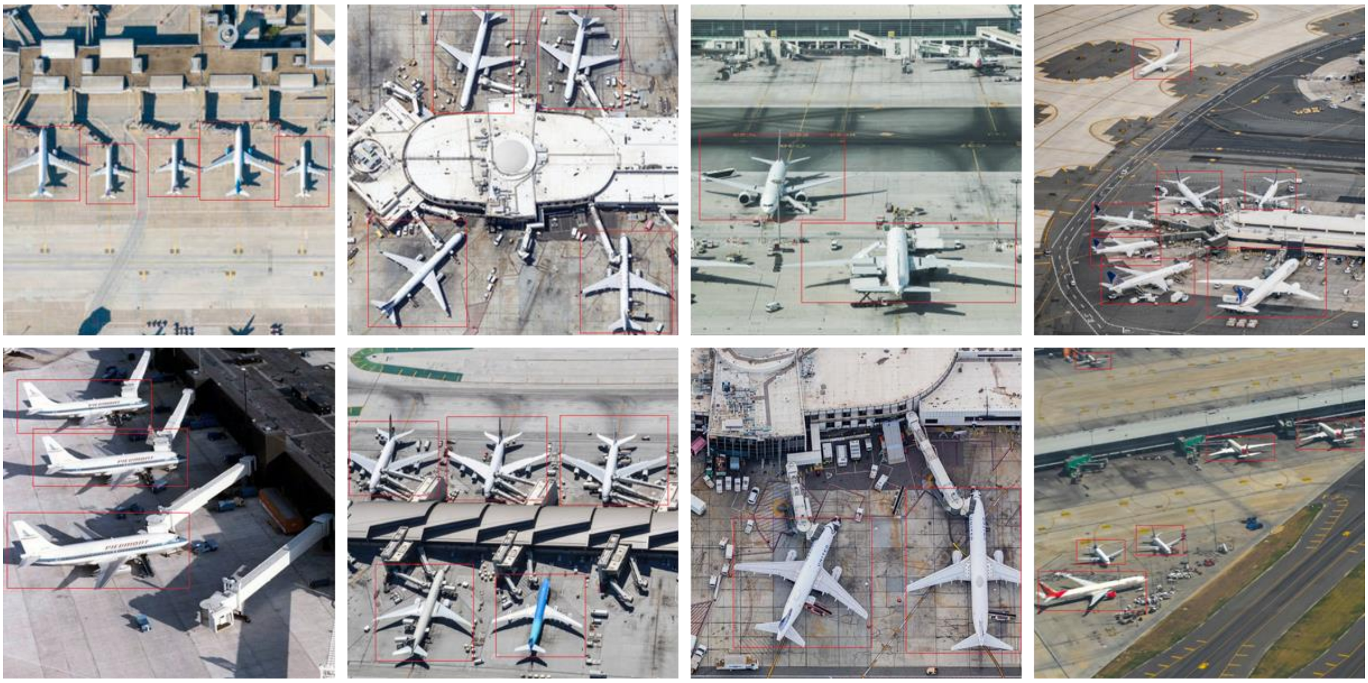

Fig. 2. Detection of aircraft at airports using the YOLOv5 algorithm.

Table 1. Performance comparison of YOLOv5, YOLOv4, and SSD algorithms for detecting aircraft at airports.

	Indicator				
Model	Precision	Recall	mAP	F1 Score	Inference S.
YOLOv5	0.759	0.772	0.766	0.765	54 ms
YOLOv4	0.671	0.624	0.641	0.647	67 ms
SSD	0.715	0.683	0.703	0.699	48 ms

these models matches the precision of YOLOv5, highlighting YOLOv5's advantage in effectively minimizing false alarms during detection. When examining recall, YOLOv5 again leads with a value of 0.772, closely followed by SSD at 0.683 and YOLOv4 at 0.624. Recall measures the algorithm's ability to correctly identify all instances of aircraft in the images. YOLOv5's higher recall suggests that it is better at detecting aircraft across various conditions and settings, capturing more true positives compared to YOLOv4 and SSD. While SSD performs moderately well, the noticeable gap between its recall value and that of YOLOv5 points to SSD occasionally missing certain aircraft, especially when compared to the more advanced detection capabilities of YOLOv5. YOLOv4, on the other hand, has the lowest recall among the three, implying that it struggles the most with detecting aircraft comprehensively in the given dataset. This could be due to YOLOv4's architecture being less optimized for complex airport environments or diverse conditions present in the test images.

The mean average precision (mAP), which combines both precision and recall across multiple confidence thresholds, further solidifies YOLOv5's dominance, with a value of 0.766. mAP serves as a balanced metric that evaluates the model's overall detection performance. YOLOv5's higher mAP suggests that it strikes a better balance between precision and recall, making it the most reliable algorithm for the detection task. SSD comes in second with an mAP of 0.703, indicating that while it performs well, it lacks the consistency of YOLOv5 across different detection thresholds. YOLOv4's mAP, at 0.641, is notably lower, further reflecting the algorithm's struggles with both precision and recall. This gap in mAP between YOLOv5 and YOLOv4 indicates that YOLOv5's architectural improvements allow for more consistent and accurate detection, while YOLOv4 shows a tendency to miss objects or produce false positives under certain conditions. The F1 score, which is the harmonic mean of precision and recall, offers another perspective on the overall performance. YOLOv5's F1 score of 0.765 showcases its ability to maintain a strong balance between detecting all aircraft and minimizing false positives, further affirming its robustness as an object detection model. SSD follows with an F1 score of 0.699, showing that it is also fairly well-balanced but still falls short of YOLOv5's performance, particularly in terms of handling challenging or complex detection scenarios. YOLOv4, with the lowest F1 score of 0.647, underscores its overall weaker performance in terms of precision-recall balance. These values make it clear that YOLOv5's improved architecture leads to more accurate and reliable detection, while YOLOv4's older design struggles to keep up in terms of both metrics.

When evaluating inference speed, which is a critical factor for real-time applications such as aerial monitoring and airport security, SSD offers the fastest detection with an inference time of 48 ms. This suggests that SSD is better suited for scenarios where speed is the primary concern, though its reduced accuracy compared to YOLOv5 may make it less suitable when precise detection is required. YOLOv5, with an inference speed of 54 ms, offers a strong balance between speed and performance, making it ideal for real-time detection tasks where both accuracy and response time are critical. YOLOv4, with an inference speed of 67 ms, is the slowest of the three, further detracting from its suitability for timesensitive applications. The performance gap between YOLOv5 and YOLOv4 in terms of speed reflects YOLOv5's more efficient processing capabilities, which have been optimized to provide quicker detection without sacrificing accuracy. Thus, the results from Table 1 clearly indicate that YOLOv5 outperforms both YOLOv4 and SSD in most metrics, making it the most suitable algorithm for detecting aircraft at airports in this study. YOLOv4 lags behind in every metric, reflecting its older architecture and less efficient detection capabilities. SSD, while faster in terms of inference speed, sacrifices some accuracy, making it a suitable option only when real-time detection speed is a priority and minor reductions in accuracy are acceptable.

IV. CONCLUSION

In this study, the YOLOv5 algorithm was evaluated for its effectiveness in detecting aircraft at airports, with its performance compared to the YOLOv4 and SSD algorithms. The results demonstrate that YOLOv5 outperforms both YOLOv4 and SSD across key metrics, including precision, recall, mAP, and F1 score, establishing it as the most reliable algorithm for this specific application. YOLOv5 exhibited the highest detection accuracy, successfully identifying aircraft in various challenging conditions with a well-balanced precision-recall tradeoff. Additionally, its inference speed, while slightly slower than SSD, remains highly competitive and suitable for real-time detection tasks. SSD, although delivering the fastest inference speed, showed a moderate reduction in detection accuracy, making it more appropriate for scenarios where speed is prioritized over accuracy. On the other hand, YOLOv4, with lower scores in all performance metrics, proved to be the least effective algorithm in this comparison, hindered by its slower processing time and lower detection accuracy.

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