

Remote Sensing-based Automated Civil Aircraft Detection using YOLOv8 Architecture

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Abstract— Detection of aircraft from satellite images is a critical activity in air traffic observation, airport operations, and air safety. Conventionally, the detection of aircraft is based on manual examination or traditional machine learning methods, which are challenged with coping with variation in aircraft shape, orientation, and weather conditions. In this paper, we introduce a deep learning approach based on the YOLOv8 object detection model to identify civil aircraft from high-resolution satellite images. Although several existing models like Faster R-CNN, SSD, and previous YOLO versions have been used for object detection tasks, YOLOv8 offers practical improvements. It simplifies the detection pipeline by removing anchor boxes, uses a cleaner architecture, and provides better training stability. The current work targets testing the model using accuracy metrics like mean Average Precision (mAP) and Intersection over Union (IoU) and comparisons with other deep learning models. The model has achieved an accuracy of 91% and false positive rate of 0.31%. The objective of this research is to make a contribution to automated satellite image-based aircraft detection, with possible implications in real-time aviation surveillance and operational planning.

Index Terms— Aircraft detection, satellite imagery, air traffic monitoring, aviation safety, airport management, deep learning, Convolutional Neural Network (CNN), YOLO, object detection, machine learning, automated detection, real-time monitoring.

I. INTRODUCTION

Recognition of aircraft from satellite imagery is critically important for monitoring air traffic, border security, and emergency relief. Automatic identification of civilian aircraft is essential to provide assistance to autonomous systems controlling air space security and logistics. Traditional object-based detection methods are unreliable with variation in aircraft size, orientation and clutter variations in the satellite images.

Recent advancements in deep learning have led to the development of object detection models that yields remarkable results.

Among these, the YOLO (You Only Look Once) model stands out for its balance between speed and accuracy. In this paper we utilized YOLOv8, a recent version of the YOLO framework, to detect civil aircraft from satellite imagery. Although various deep learning models have been proposed in literature, YOLOv8 offers distinct advantages including a streamlined architecture, better inference efficiency, and improved detection accuracy.

A. Motivation

As the satellite imaging technology is evolving rapidly, the potential to monitor and analyze airborne targets like civilian aircraft has gained tremendous value in various applications including air traffic management, defense surveillance, and disaster response. The traditional process of analyzing satellite images is slow, prone to error, and is not much scalable. This study is inspired by adapting and fine-tuning deep learning methods particularly to detect civil aircrafts within satellite images to deliver accuracy, velocity, and versatility in practical settings.

B. Problem Statement

The accurate recognition of civil aircraft in satellite images remains a challenge despite the advancement of object detection technology. This is due to difficulties such as aircraft sizes, orientations, lightning conditions, and complex backgrounds. Furthermore, there exists limited research on developing lightweight CNN models for aircraft detection. This study focuses on developing an accurate and reliable civil aircraft detection system.

C. Objectives

- To implement YOLOv8 model for aircraft detection in optical satellite images.
- To evaluate the proposed model's performance using mAP, precision, recall, and F1-score.
- To collect and preprocess a satellite imagery dataset containing civil aircraft.

II. LITERATURE REVIEW

Jin et al [1] discussed the YOLOv7-Tiny model by integrating it with a Multi-Head Dynamic Joint Self-Attention mechanism and GS_SPPCSPC module to enhance feature extraction in aircraft detection from remote sensing images. While efficient and lightweight, it may struggle with fine-grained object boundaries under severe occlusion due to feature simplification. Shaar et al [2] proposed a U-Net-based architecture for semantic segmentation to detect aircraft in satellite images. It displays high segmentation accuracy, requiring fewer labeled data due to effective skip connections. The model performs well for pixel-level classification but unable to generate bounding boxes. Xie et al [3] presented a deep CNN with multi-scale feature fusion designed to detect small, fine-grained objects like aircraft in satellite imagery. The model excels in complex scenes by capturing subtle features at varied scales but its computational cost is high. Polat et al [4] proposes a learning-based method using Gabor filters for feature extraction and Support Vector Machines (SVM) for classifying stationary aircraft from satellite imagery. This approach uses the geometric structure of aircraft for accurate detection but its dependency on manual features and traditional classifiers. Alganci et al [5] discussed various CNN-based object detection methods for aircraft detection in very high-resolution satellite images, including Faster R-CNN and YOLOv3. The study shows that deep learning models outperform traditional feature-based techniques in both accuracy and robustness. El Ghazouali et al [6] FlightScope benchmarks multiple detection models including Faster R-CNN, CenterNet, using the HRPlanesV2 and GDIT datasets for aircraft identification. The study finds YOLOv5 to offer the best balance of accuracy and inference time. Ren et al [7] discussed YOLOv3 with annotated boxes for detecting small aircraft in remote sensing images. It highlights YOLOv3's speed and accuracy compared to Faster R-CNN and SSD. The model still struggles with overlapping targets and is sensitive to background clutter. Wu et al [8] introduces a lightweight object detector by optimizing YOLOv5 using Lite backbones, efficient loss functions, and BSG-FPN modules. The model shows improved AP achieving competitive results on RSOD and DIOR datasets. The model may face difficulties with generalization across unseen environments.

Recent studies have applied deep learning for aircraft detection in remote sensing imagery. Traditional approaches using handcrafted features and SVM classifiers lacked adaptability to variations in aircraft shape and background clutter. The YOLO series introduced a unified detection framework balancing speed and precision. While YOLOv5 and YOLOv7 achieved good performance, they still struggled with small aircraft and overlapping targets. Recent works using U-Net and multi-scale CNNs improved feature extraction but were less efficient for real-time detection. Hence, this study adopts the YOLOv8 architecture for its anchor-free detection head, lightweight structure, and strong feature fusion capability, providing higher accuracy and faster inference for high-resolution satellite images.

III. PROPOSED SYSTEM

The proposed system employs a YOLOv8-based deep learning model to detect civil aircraft in satellite images. The workflow includes image preprocessing, model training, detection, and evaluation. The HRPlanesV2 dataset containing annotated aircraft images is used, with all images resized and normalized for consistency.

YOLOv8's CSPDarknet backbone extracts multi-level spatial features, while the FPN-PAN neck fuses them for robust detection of aircraft at different scales. Its anchor-free detection head directly predicts bounding boxes and confidence scores, reducing computation and improving localization accuracy.

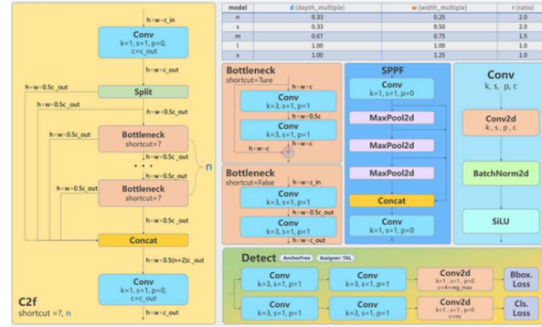


Figure 1. Proposed System Architecture

The proposed system identifies aircraft in high-resolution satellite imagery through an optimized YOLOv8-based architecture. The HRPlanesv2 dataset, containing images of civilian aircraft as well as corresponding YOLO-format annotation files, is particularly utilized to train the system. The arrangement of the architecture's head, neck, and backbone provides a robust structure for efficient and accurate object detection at varying image scales. The backbone network employs CSPDarknet, which takes advantage of convolutional layers and residual connections to effectively extract both low-level and high-level features. These features help determine an aircraft's structure, shape, and surface texture from the aerial view. A Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) architecture form the neck module. The part increases the system's capability to detect aircraft of different sizes and resolutions by combining spatially dense features from shallow layers with semantic-dense features from deeper layers.

Despite partial occlusion or cluttered backgrounds, the design allows accurate identification of the aircraft. Training efficiency and overall generalization are improved by employing mixed precision training and sophisticated augmentation methods. In conclusion, the proposed structure provides an efficient and scalable approach to automatically identify civil aircraft from satellite imagery.

The approach to constructing the automated civil aircraft detection system is organized into major phases: dataset preparation, annotation, model construction, training, and testing.

A. Dataset Preparation

The HRPlanesv2 dataset, which contains high-resolution satellite imagery of civil aircraft, was chosen for validation and training. The dataset is provided with RGB imagery as well as annotation files in YOLO format with each annotation identifying the class label and normalized bounding box coordinates. For robust performance of the models, the data was divided into training and validation sets in the ratio 80:20. All the images are resized to 512x512 pixels since dataset contains different sized images. Corrupted image files were also inspected, and background images without aircraft were kept to enhance model discrimination.

Sample Dataset Images



Figure 2. Preview of images in the dataset

B. Annotation

Every image from the HRPlanesv2 dataset comes with an YOLO format annotation file. The YOLO format demands that bounding boxes be stated in the form of normalized values with respect to the dimensions of the image.

Where all values are normalized using the following formulas:

$$x_{center} = \frac{x_{min} + x_{max}}{2W} \quad (1)$$

$$y_{center} = \frac{y_{min} + y_{max}}{2H} \quad (2)$$

$$y_{center} = \frac{y_{min} + y_{max}}{2H} \quad (3)$$

$$y_{center} = \frac{y_{min} + y_{max}}{2H} \quad (4)$$

Here, W and H denote the width and height of the image, and $x_{min}, y_{min}, x_{max}, y_{max}$ represents the pixel coordinates of the bounding box. This normalization ensures consistency across different image sizes and improves model generalization.

C. Model Creation

The light model structure and competitive performance of YOLOv8n (nano) architecture rendered it a suitable model for deployment on high-resolution satellite images. To expedite convergence, pretrained weights have been employed to initialize the model, and the number of classes (nc) was fixed at 1 to tailor it to single class detection. Its backbone, CSPDarknet, effectively extracts low-level and high-level spatial features with residual connections and cross-stage partial networks.

The neck, which includes a Feature Pyramid Network (FPN) and Path Aggregation Network (PAN), combines multi-scale features. An anchor-free detection head provides efficient, precise object localization with less computational overhead.

The model uses a multi-component loss function, expressed as:

$$L = L_{\{obj\}} + L_{\{cls\}} + L_{\{bbox\}} \quad (5)$$

$L_{\{obj\}}$ is the objectness loss, $L_{\{cls\}}$ is the classification loss, and $L_{\{bbox\}}$ (6) is the bounding box regression loss. The bounding box loss is calculated using:

$$L_{bbox} = \lambda_{coord} \sum_i \left(I_i \cdot (|x_i - \hat{x}_i| + |y_i - \hat{y}_i| + |w_i - \hat{w}_i| + |h_i - \hat{h}_i|) \right) \quad (6)$$

D. Training and Testing

Adam optimizer is employed while training and testing to maximize loss function. Sigmoid function is applied at the layers of the model used for output layer binary classification whereas ReLU function at hidden layers. Weights are also updated during the training process based on gradients using backpropagation. The learning rate plays a significant part and often scheduled to decline. In training, the model is tested on unseen images, accuracy and loss are computed, and hyperparameters are tuned if necessary for best performance.

E. Evaluation of Model's Performance

Model performance was assessed by comparing ground truth annotations and predicted bounding boxes using Intersection over Union (IoU). IoU of 0.5 was used to count True Positives (TP), False Positives (FP), and False Negatives (FN). From these values, Accuracy, false positive rate (FPR) and loss functions were derived in eq(7) to eq (11). Efficient object detection performance is characterized by high accuracy and low FPR.

$$Accuracy = \frac{TP}{TP+FP+FN} \quad (7)$$

$$FPR = \frac{FP}{FP+T} \quad (8)$$

$$\text{Total Loss} = \text{Box Loss} + \text{Cls Loss} + \text{DFL Loss} \quad (9)$$

$$\text{Box Loss} = 1 - \text{IoU}(\text{pred}, \text{gt}) \quad (10)$$

$$\text{Cls Loss} = - \sum [y \cdot \log(\hat{y}) + (1 - y) \cdot \log(1 - \hat{y})] \quad (11)$$

IV. RESULTS AND ANALYSIS

TABLE I: COMPARISON WITH OTHER MODELS

Model	Dataset	Accuracy (AP/mAP)
YOLOv8(nano)	HRPlanesV2	91.52%
YOLOv10	HRPlanesV2 + GDIT	90.7%
SSD	DOTA/Large Scale	76%(F1 Score)
RetinaNet + SwinT	HRPlanes	87.4%AP
RC2CNN with FPN	NWPU VHR-10 dataset	88.93% AP

For both training and validation datasets, the loss curves show a steady decrease over 20 epochs for each of the three components (Box Loss, Class Loss, and DFL Loss). As the model learns, the training and validation losses—especially the Box and Class losses—progressively drop from their initial higher levels. There is quite minimal overfitting, as observed by the training and validation curves following each other closely. All loss values tend to converge below 0.9 at the final epoch and the validation losses tend to resemble the training losses closely. This trend indicates consistent learning dynamics and effective model generalisation. The model performs reasonably well in all the primary loss indicators and shows robust convergence behaviour across the board.

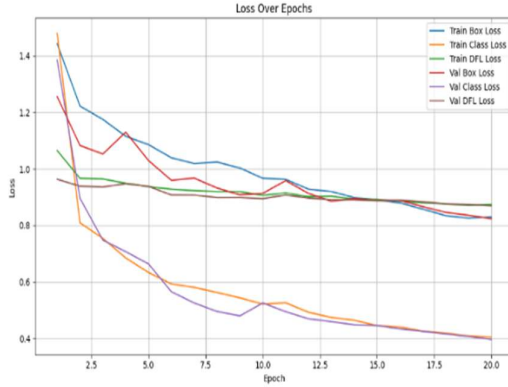


Figure 3. Model Loss

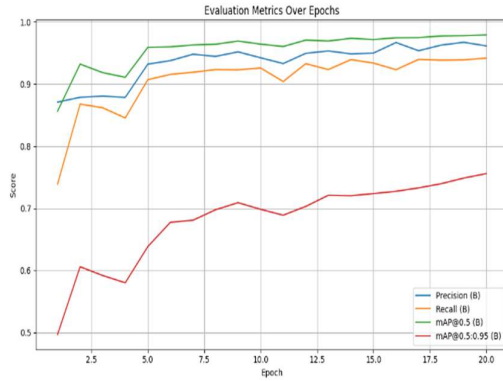


Figure 4. Model Accuracy



Figure 5. Output of the model

V. CONCLUSION AND FUTURE WORK

The model proposed here based on YOLOv8 architecture on the HRPlanesv2 dataset with a precision of 91.52% at 0.41 false positive rate demonstrates good performance on high-resolution satellite imagery. The model delivers improved precision and efficiency. Future performance can be improved by utilizing larger datasets, minimizing false detections by post-processing, and integration into existing aircraft surveillance systems for real-time use.

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