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# Real-Time Aircraft Target Detection Using Improved Yolov7-Tiny Network

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## Abstract
*Detecting aircraft from remote sensing images has become increasingly important in applications such as military surveillance, airspace monitoring, airport management, and disaster response. However, identifying aircraft in satellite imagery is not straightforward. The objects are often small in size, surrounded by complex backgrounds, and affected by variations in lighting and resolution. Traditional object detection approaches and computationally heavy deep learning models either lack accuracy or fail to achieve real-time performance. Traditional computer vision techniques based on handcrafted features lack robustness and adaptability to such diverse conditions. Although deep learning-based object detection models have achieved remarkable success in natural image datasets, their direct application to remote sensing imagery does not always yield optimal performance, particularly for small object detection. Lightweight models designed for real-time inference often sacrifice detection accuracy to maintain speed. In this study, we propose an improved lightweight detection framework based on YOLOv7 tiny architecture for real-time aircraft detection in remote sensing images. The proposed method enhances multi-scale feature extraction and optimizes anchor box configurations to improve small-target detection performance while preserving computational efficiency. The model is implemented using Py-Torch and trained on annotated aircraft datasets. Experimental results demonstrate improved precision, recall, and mean Average Precision (map) compared to conventional lightweight detectors. The proposed system achieves a balance between detection accuracy and inference speed, making it suitable for practical real-world surveillance applications.*
***Keywords:*** *Aircraft Detection, Remote Sensing, YOLOv7-Tiny, Deep Learning, Real-Time Detection, Small Object Detection.*

## 1. Introduction
The rapid advancements of satellite imaging technologies, remote sensing data has become more accessible and detailed than ever before. Extracting meaningful information from such high-resolution images is a challenging yet essential task. Among various applications, aircraft detection plays a critical role in defense surveillance, border security, and airspace management. Traditional computer vision techniques relied heavily on handcrafted features and manual analysis. Although these methods worked in controlled environments, they often struggled in complex real-world scenarios. The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), significantly improved object detection accuracy. Single-state detection models such as YOLOv7 have gained popularity because of their ability to perform detection in real time. The lightweight version, YOLOv7-Tniy, is designed for faster inference and lower computational requirements. However, when applied to remote sensing images, detecting small and densely distributed aircraft remains challenging. Remote sensing technology has advanced significantly in recent years due to improvements in satellite imaging systems and aerial surveillance platforms. High-resolution satellite imagery is now widely used in various applications such as environmental monitoring, disaster management, urban planning, military intelligence, and national security. Among these applications, aircraft detection has emerged as a critical task, particularly in defense surveillance, airport monitoring, border security, and airspace

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management. The ability to accurately detect and localize aircraft in satellite images enables authorities to monitor air traffic, identify unauthorized aircraft movement, and strengthen national security measures. This Despite its importance, aircraft detection in remote sensing images presents several challenges. Unlike conventional object detection tasks performed on natural images, remote sensing imagery typically contains large-scale scenes where objects occupy only a small portion of the image. Aircraft often appears as small clusters of pixels within high-resolution backgrounds, making them difficult to identify accurately. Furthermore, complex surroundings such as buildings, runways, vehicles, and shadows increase the possibility of false detections. Variations in scale, orientation, illumination, and atmospheric conditions further complicate the detection process. Manual inspection of large volumes of satellite data is time-consuming and prone to human error, emphasizing the need for automated and intelligent detection system. Traditional object detection methods relied heavily on handcrafted features and classical machine learning techniques. These approaches used manually designed descriptions such as edges, textures, and color histograms to represent objects. Although they performed reasonably well in controlled environments, their effectiveness diminished when applied to complex real-world scenarios such as remote sensing imagery. The limitations of handcrafted feature extraction motivated the adoption of deep learning techniques, particularly Convolutional Neural Networks (CNNs), which automatically learn hierarchical feature representations directly from raw image data. This shift significantly improved detection performance and robustness across various computer vision applications. Deep learning-based object detection models are broadly categorized into two-stage and single-stage detectors. Two-stage detectors, such as Faster R-CNN, first generate region proposals and then classify each proposed region. While these models achieve high accuracy, they involve complex architectures and require substantial computational resources. Their relatively slower inference speed makes them less suitable for real-time surveillance systems, where rapid response is essential. To address this limitation, single-stage detectors were introduced. These models perform object localization and classification simultaneously in a single forward pass through the network, thereby achieving faster detection speeds. Among the single-stage detectors, YOLOv7 represents one of the most recent advancements in the YOLO (You Only Look Once) family. It demonstrates significant improvements in detection accuracy and computational efficiency. YOLOv7 introduces architectural optimizations that enhance feature extraction and learning capability while maintaining real-time performance. A lightweight variant, YOLOv7-Tiny, is specifically designed for scenarios where computational resources are limited. Its reduced parameter size and simplified architecture enable deployment on edge devices and systems requiring faster inference. However, when applied to remote sensing images, lightweight detection models often face difficulties in identifying small objects such as aircraft. During the convolution and down sampling processes, fine-grained spatial details may be lost, reducing the model's ability to detect small targets accurately. Since aircraft in satellite images frequently occupy a very small region of the overall image, preserving detailed feature information is crucial. Additionally, aircraft may appear in different orientations and scales, requiring robust multi-scale feature extraction mechanism. The dense distribution of aircraft in busy airport environments further increases the complexity of precise localization. Another major challenge in remote sensing-based aircraft detection is background similarity. Airports and urban regions contain structures that visually resemble aircraft shapes, such as parked vehicles, building rooftops, and runway markings. Without strong feature discrimination capability, detection models may generate false positives. Therefore, enhancing feature fusion strategies and improving the detection head design are essential for achieving reliable performance. In real-world deployment scenarios, detection systems must satisfy multiple constraints simultaneously. They must provide high detection accuracy to minimize false alarms, operate at real-time speed for immediate decision-making, and maintain low computational complexity for practical implementation. Achieving a balance among these factors is particularly challenging in small-object detection tasks. High-capacity models may offer improved accuracy but are computationally expensive, whereas lightweight models may sacrifice detection precision. Hence, there is a clear need to improve lightweight architectures so that they can effectively detect small aircraft while preserving real-time capacity. The proposed work addresses these challenges by enhancing the YOLOv7-Tiny architecture to improve its sensitivity toward small aircraft targets in remote sensing images. The focus of this research is on strengthening multi-scale feature representation and improving feature fusion mechanisms without significantly increasing computational overhead. By refining the detection process, the system aims to achieve better precision and recall performance in complex satellite imagery. The implementation of the proposed model is carried out using Porch, a widely adopted deep learning framework known for its flexibility and efficient GPU acceleration. This flexibility supports the development of customized detection models tailored to aircraft detection requirements.

## 2. Literature Review

Detecting small objects in remote sensing imagery remains one of the most difficult problems in computer vision. Aircraft captured in satellite images often occupy only a few pixels, which leads to loss of critical spatial features during deep network down sampling. Researchers have observed that standard convolutional layers tend to reduce feature map resolution, making it harder for models to identify small-scale objects accurately. To overcome this issue, multi-scale feature fusion strategies such as Feature Pyramid Networks (FPN) have been widely adopted. These approaches combine low-level detailed features with high-level semantic information, improving detection performance for small targets. Recent YOLO-based models incorporate similar strategies to enhance small object recognition. Several benchmark datasets have been developed for aircraft detection research. Public datasets such as DOTA (Dataset for Object Detection in Aerial Images) and NWPU VHR-10 have played a significant role in evaluating detection algorithms. Studies conducted using these datasets show that lightweight single-stage detectors can achieve competitive accuracy when properly optimized. Dense aircraft distribution Occlusion and shadow effects Similar background textures (runways, buildings, roads) This highlights the importance of customizing detection models specifically for aerial image characteristics. The YOLO framework has evolved significantly from its earlier versions to its recent advancements. Early versions focused mainly on speed, sometimes at the cost of accuracy. Later improvements introduced better backbone networks, anchor box optimization, and improved loss functions. The release of YOLOv5 introduced efficient model scaling and improved training strategies. Subsequently, YOLOv7 further optimized the architecture by introducing extended efficient layer aggregation networks and re-parameterization techniques. Despite these improvements, research indicates that the tiny variants of these models require additional tuning to perform effectively on small aerial targets. This motivates the modification of YOLOv7-Tiny for specialized aircraft detection.

## 3. Proposed Methodology

The proposed methodology focuses on enhancing the detection capability of the YOLOv7-Tiny model specifically for aircraft targets in remote sensing images. Unlike general object detection problems, aircraft detection in aerial imagery presents unique challenges such as small object size, dense object distribution, background clutter, and scale variation. Therefore, the methodology is carefully structured to address these challenges in a systematic manner. Initially, remote sensing images containing aircraft are collected and properly annotated using bounding boxes. Each aircraft instance is labeled to ensure accurate supervised learning. The dataset then undergoes preprocessing, which includes resizing images to a uniform input dimension, normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, scaling, and brightness adjustment. These preprocessing steps enhance the robustness of the model and improve its ability to generalize across varying environmental conditions. The core of the proposed methodology

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lies in enhancing the YOLOv7-Tiny architecture. Although YOLOv7-Tiny is a lightweight and fast object detection model, its default configuration may not optimally capture fine-grained features of small aircraft in high-resolution images. Therefore, the model is improved by strengthening feature extraction layers, optimizing anchor box sizes based on dataset characteristics, and enhancing multi-scale feature fusion. These modifications enable the network to retain more spatial information and detect small targets more effectively. The improved model is trained using a deep learning framework with GPU acceleration to ensure faster convergence. During training, the loss function combines bounding box regression loss, objectness loss, and classification loss to optimize detection accuracy. Hyperparameters such as learning rate, batch size, and number of epochs are carefully tuned to achieve stable performance and avoid overfitting. Finally, the trained model is evaluated using standard performance metrics including precision, recall, F1-score, and mean Average Precision (mAP). The system is then tested in real-time detection scenarios where aircraft are identified with bounding boxes and corresponding confidence scores. The proposed methodology ensures a balance between detection accuracy and real-time performance, making it suitable for surveillance, defense monitoring, and airport management applications.

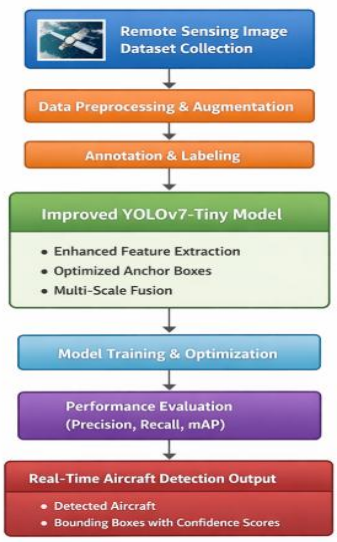


**Figure 1 Proposed System**

## 4. Results and Discussion

The proposed aircraft detection system was evaluated using a dataset of remote sensing images containing aircraft objects with different orientations, sizes, and background environments. The improved model based on YOLOv7 was trained and tested to analyze its ability to accurately detect aircraft in complex aerial imagery. During the training phase, the model gradually improved its detection capability as the number of epochs increased. The loss values decreased consistently, indicating that the model successfully learned important visual features associated with aircraft objects. After completing the training process, the system was tested on unseen images to evaluate its generalization performance. The experimental results show that the proposed system can effectively identify aircraft objects The model generates bounding boxes around detected aircraft along with confidence scores indicating the probability of correct detection. To measure the effectiveness of the proposed system, several evaluation metrics were used. These metrics provide a comprehensive understanding of the detection accuracy and reliability of the model. Precision represents the proportion of correctly detected aircraft among all detected objects. A higher precision value indicates fewer false detections. The improved architecture demonstrates strong detection capability across multiple scenarios. The model successfully identifies aircraft targets even when the background contains complex structures such as buildings, roads, or runways. The improvements introduced in the feature extraction and multi-scale feature fusion stages help the model capture fine-grained spatial details. This is particularly important in remote sensing images where aircraft objects occupy only a small portion of the overall image. Another key advantage of the proposed model is its real-time detection capability. Because the system uses a lightweight architecture, it requires less computational power while maintaining good accuracy. This makes the model suitable for real-world surveillance systems where quick response times are essential. Traditional object detection methods and two-stage detection models such as Faster R-CNN typically provide high accuracy but require significant computational resources and longer inference times. This makes them less suitable for real-time applications. These characteristics make the proposed system more practical for applications such as defense surveillance, airport monitoring, and aerial reconnaissance.

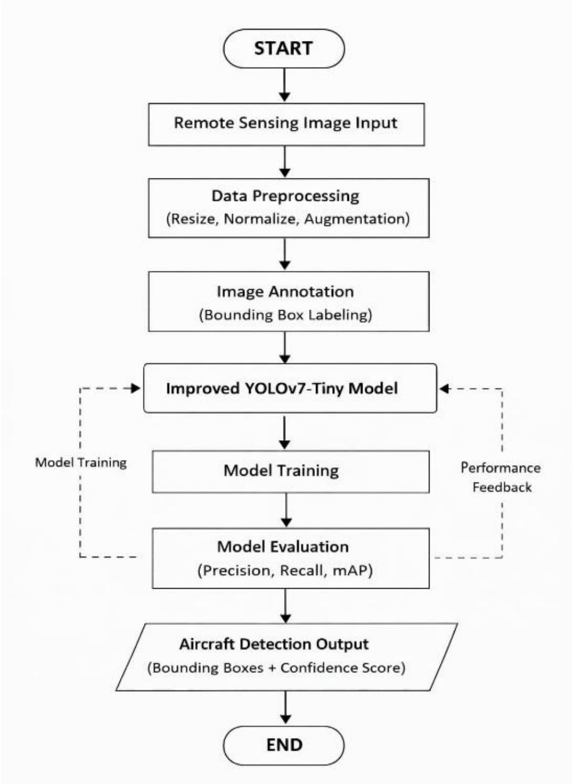


**Figure 2 Flow chart**

## Conclusion

In this study, an efficient aircraft detection system based on an improved version of YOLOv7 Tiny architecture was proposed for analyzing remote sensing images. Detecting aircraft in aerial imagery is a challenging task due to small object sizes, complex backgrounds, and variations in orientation and lighting conditions. The proposed approach focuses on enhancing the detection capability of the lightweight YOLOv7-Tiny model by improving feature extraction and optimizing detection strategies for small targets. The experimental results demonstrate that the model is capable of accurately identifying aircraft objects while maintaining fast processing speed, which is essential for real-time surveillance applications. Compared with traditional object detection models such as Faster R-CNN, the proposed system offers a better balance between computational efficiency and detection accuracy. The results indicate that the improved model performs reliably even in challenging environments where aircraft objects appear small or partially occluded. Therefore, the proposed system can be effectively applied in practical domains such as defense surveillance, airport monitoring, airspace security, and disaster management. In future work, the system can be further enhanced by incorporating larger and more diverse datasets, integrating advanced attention mechanisms, and extending the model to detect multiple types of aerial objects. These improvements may further increase the robustness and adaptability of the system for real-world remote sensing applications. Furthermore, the proposed aircraft detection framework demonstrates the potential of deep learning–based object detection techniques for analyzing high-resolution remote sensing imagery. By utilizing the lightweight architecture of YOLOv7 Tiny, the system is able to process aerial images efficiently while maintaining satisfactory detection accuracy. The study highlights how improvements in multi-scale feature extraction and optimized training strategies can significantly enhance the detection of small objects such as aircraft in satellite images. The results obtained from the experimental analysis confirm that the proposed method can operate effectively in practical environments where rapid and reliable detection is required. With further improvements in dataset diversity and model optimization, the proposed system has strong potential to support intelligent surveillance systems and automated aerial monitoring platforms in the future.

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