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Review Study of Satellite Image-Based Airbase Surveillance and Monitoring Using YOLOv8

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Abstract: *Airbase surveillance is essential for national defense and strategic monitoring. Traditional surveillance techniques rely on manual interpretation of satellite imagery, which is slow and error-prone. Recent advances in deep learning have enabled automated aircraft detection in remote sensing images. Among modern detectors, YOLOv8 provides a strong balance between speed and accuracy. This paper presents a comprehensive review of satellite image-based airbase surveillance systems with emphasis on YOLOv8. Existing methods, datasets, system architectures, challenges, and future directions are analyzed. The review highlights research trends and opportunities for building scalable and real- time airbase surveillance systems.*

Keywords: Airbase Surveillance, Satellite Imagery, Object Detection, YOLOv8, Deep Learning, Aircraft Detection

I. INTRODUCTION

Airbase surveillance is a critical cornerstone of national security and military readiness, providing essential intelligence on combat fleets and strategic infrastructure [1]. Traditionally, this task relied on manual inspection of satellite imagery by human analysts, a process that is time-consuming and prone to error [2]. With the rapid growth of high-resolution satellite imagery, manual monitoring has become increasingly impractical for large-scale operations.

To address these limitations, research has shifted toward automated image analysis using deep learning techniques [3]. Convolutional Neural Networks (CNNs) have demonstrated significant success in object detection tasks, enabling automatic feature learning directly from raw imagery [4]. Two-stage detectors such as Faster R-CNN provide high localization accuracy but are computationally intensive [5]. Single-stage detectors such as SSD and YOLO offer faster inference, making them suitable for real-time surveillance applications [6]. Among these, recent advancements such as YOLOv8 introduce anchor-free detection mechanisms that improve small-object detection performance in satellite imagery [7]. Experimental studies confirm that YOLO-based architectures achieve an effective balance between accuracy and speed for remote sensing applications [8].

Despite these advancements, challenges remain in achieving robust generalization across diverse geographic conditions and in developing integrated surveillance frameworks that combine detection, counting, and visual intelligence.

II. REVIEW MOTIVATION

The rapid growth of high-resolution satellite imagery has created new opportunities for large-scale airbase monitoring and strategic intelligence extraction [1]. However, the increasing volume of data has made manual inspection impractical, highlighting the need for automated aircraft detection systems [2].

While early object detection approaches achieved moderate success, modern deep learning architectures have significantly improved detection accuracy and efficiency [3]. Among contemporary object detectors, YOLO- based models have emerged as a preferred choice for real-time applications due to their balance between speed and precision [4]. The recent introduction of YOLOv8, with its anchor- free architecture and enhanced feature learning capabilities, further improves detection performance for small and densely packed objects commonly found in satellite imagery [5].

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Despite these advancements, existing studies often focus solely on detection accuracy without addressing system-level integration, dataset diversity, and deployment challenges across varying geographic and environmental conditions. Furthermore, limited research comprehensively analyzes how recent architectural improvements translate into practical airbase surveillance capabilities.

Therefore, this review is motivated by the need to systematically evaluate existing aircraft detection approaches, analyze the evolution of YOLO-based models, and identify research gaps that must be addressed to build scalable, reliable, and real-time satellite-based airbase surveillance systems.

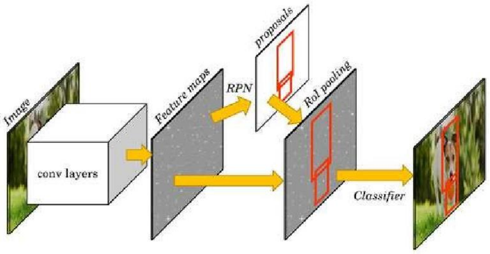

Fig. 1. General architecture of a deep learning-based object detection framework illustrating backbone feature extraction, heatmap generation, embedding offsets, and bounding box localization for accurate object detection.

III. REVIEW CONTRIBUTIONS

This review provides a structured and comprehensive analysis of aircraft detection techniques for satellite-based airbase surveillance, beginning with the foundational role of deep learning in remote sensing applications [1]. It traces the evolution of modern object detection architectures from two-stage detectors such as Faster R-CNN [2] to single-stage frameworks including SSD [3] and YOLO [4], highlighting how improvements in speed and efficiency have enabled practical real-time surveillance systems. The review further examines the architectural refinements introduced in later YOLO variants, particularly the anchor-free design and decoupled detection heads of YOLOv8 [5], which significantly enhance small-object detection performance in densely populated airbase environments. In addition to model-level comparisons, this work identifies key technical challenges such as limited dataset diversity, small-object representation, and cross-domain generalization, while emphasizing the importance of feature pyramid strategies for improving multi-scale detection [6]. By synthesizing prior benchmarking efforts and aircraft-specific detection studies [7], this review bridges theoretical deep learning advancements with operational airbase monitoring requirements. Overall, it contributes a cohesive understanding of how object detection models have progressed toward scalable, high-accuracy, and real-time airbase surveillance systems, while clearly outlining remaining research gaps and future development directions.

IV. RESEARCH GAP

Despite considerable advancements in aircraft detection using deep learning, several important gaps remain in current research. Although modern deep learning models have significantly improved object detection performance in remote sensing applications [8], most existing studies focus primarily on detecting individual aircraft instances rather than performing comprehensive airbase-level surveillance. They rarely provide integrated frameworks capable of detection, counting, and visual interpretation within a unified system.

Small-object detection remains a persistent challenge, particularly in satellite imagery where aircraft often occupy only a few pixels, limiting feature representation and localization accuracy [9]. In addition, dataset limitations significantly affect model generalization. Many studies rely on small or region-specific datasets, and models trained on such data often struggle to generalize across different geographic regions, sensor types, and environmental conditions [10].

Real-time or near-real-time monitoring capability is another underexplored area. While single-stage detectors such as YOLO have demonstrated strong real-time performance [11], many surveillance studies still focus on ofline satellite

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image analysis, which is insufficient for time-sensitive defense applications. Furthermore, few systems provide integrated counting mechanisms and annotated visual proof to support operational decision-making. Multi-sensor fusion using SAR, thermal, or infrared imagery also remains limited, despite its potential to improve robustness under adverse weather and low- light conditions. Deployment considerations such as edge computing, drone integration, and scalability across multiple airbases are similarly underdeveloped.

These gaps highlight the need for automated, accurate, scalable, and real-time airbase surveillance systems that leverage advanced detection architectures, diverse datasets, and integrated analysis frameworks. Addressing these limitations forms the primary motivation for continued research in this domain.

V. LITERATURE SURVEY

Aircraft detection in satellite imagery has progressed substantially over the past two decades, evolving from traditional image processing techniques to advanced deep learning–based frameworks. Early research primarily relied on handcrafted feature extraction methods such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT), combined with classical machine learning classifiers including Support Vector Machines and AdaBoost. While these approaches demonstrated moderate success in controlled environments, they lacked robustness under varying illumination, scale, and background complexity, limiting their practical applicability in large-scale satellite surveillance [1].

The introduction of Convolutional Neural Networks (CNNs) marked a significant shift in object detection research. CNNs enabled automatic hierarchical feature learning directly from raw pixel data, reducing dependence on manual feature engineering. Two-stage detectors such as Faster R-CNN incorporated Region Proposal Networks to improve localization accuracy and achieved strong performance in aircraft detection tasks. However, their computational complexity restricted their use in real-time or large-scale satellite image analysis [2].

To address these limitations, single-stage object detectors such as Single Shot MultiBox Detector (SSD) and You Only Look Once (YOLO) were developed. These architectures perform detection and classification in a single forward pass, significantly improving inference speed while maintaining competitive accuracy. YOLOv3 introduced multi-scale prediction mechanisms, enhancing the detection of small objects commonly found in remote sensing imagery [3].

Subsequent improvements in YOLO-based architectures further optimized detection accuracy and efficiency. YOLOv4 incorporated enhanced backbone networks and feature fusion strategies, while YOLOv5 improved training stability and deployment flexibility. YOLOv7 focused on architectural refinements to achieve state-of-the-art performance among real-time detectors [4].

More recently, YOLOv8 introduced an anchor- free detection mechanism and decoupled classification and regression heads, simplifying model configuration and improving convergence speed. Experimental studies demonstrate that YOLOv8 achieves higher mean Average Precision (mAP) while preserving real-time inference capabilities, making it particularly suitable for dense and small-object detection scenarios such as airbase environments [5].

Beyond model architecture, literature also highlights the importance of dataset diversity and preprocessing strategies. Public datasets such as Pascal VOC and MS COCO have supported general object detection research; however, specialized aircraft datasets remain limited. Domain shift across geographic regions and satellite sensors continues to challenge model generalization [6]. Researchers have proposed techniques such as multi-scale training, feature pyramid networks, and data augmentation to mitigate these issues and enhance robustness.

Recent studies further explore advanced topics including aircraft counting, multi-class classification, multi-sensor fusion with Synthetic Aperture Radar (SAR), and edge- device deployment for real-time surveillance applications. Comparative benchmarking analyses consistently indicate that YOLO-based architectures provide the best trade-off between detection accuracy and computational efficiency for remote sensing tasks [7].

In summary, the literature demonstrates a clear transition from handcrafted feature- based detection methods to highly optimized deep learning frameworks. Among these, YOLOv8 represents the current state of the art for real-time aircraft

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detection in satellite imagery. Nevertheless, challenges related to small-object detection, dataset limitations, and cross-domain generalization remain active research areas that require continued investigation.

VI. RELATED WORK

Early aircraft detection in satellite imagery relied on handcrafted feature extraction techniques combined with traditional machine learning classifiers. Methods based on Scale- Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG) were widely used to capture structural and edge- based characteristics of aircraft in overhead imagery [1]. Although these approaches demonstrated moderate success under controlled conditions, they struggled in complex airbase environments characterized by cluttered backgrounds, varying illumination, and scale variations.

The introduction of deep learning significantly transformed remote sensing object detection. Convolutional Neural Networks (CNNs) enabled automatic hierarchical feature learning, eliminating the need for manual feature engineering [2]. Two-stage detectors such as Faster R-CNN further improved localization accuracy by introducing Region Proposal Networks for candidate object generation [3]. These models achieved high detection precision and were successfully applied to aircraft detection tasks in high- resolution satellite imagery. However, their computational complexity limited their applicability for real-time surveillance and large-scale monitoring.

To address efficiency limitations, single-stage detectors such as SSD were proposed, providing faster inference while maintaining competitive accuracy [4]. The YOLO framework advanced this approach by formulating detection as a unified regression problem, significantly improving real-time processing capability [5]. Subsequent versions, including YOLOv3 and YOLOv4, introduced multi-scale feature extraction, improved backbone networks, and optimized training strategies, leading to better performance for small-object detection in satellite images [6]. These improvements were particularly important for airbase monitoring, where aircraft often occupy only a small fraction of the image.

Recent research has focused on further enhancing detection performance for very high-resolution (VHR) imagery. Comparative studies have demonstrated that YOLO-based architectures provide an optimal trade-off between detection accuracy and inference speed for remote sensing applications [7]. The latest advancement, YOLOv8, introduced anchor-free detection mechanisms and decoupled heads for classification and regression, improving convergence speed and small-object localization accuracy [8]. Experimental evaluations indicate that YOLOv8 achieves superior mean Average Precision (mAP) while maintaining real-time performance, making it highly suitable for automated airbase surveillance systems.

Despite these advancements, most existing studies concentrate on isolated aircraft detection rather than comprehensive airbase- level monitoring frameworks. Integrated systems capable of detection, counting, visualization, and deployment scalability remain limited, highlighting the need for structured surveillance pipelines built upon advanced real-time detectors such as YOLOv8.

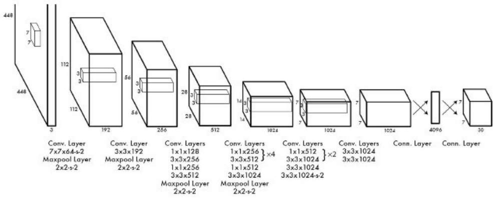

Fig. 2. Architecture of aircraft detection models compared in FlightScope study.

VII. YOLOV8 FOR AIRCRAFT DETECTION

Introduces an anchor-free detection head and improved backbone architecture. It employs multi-scale feature extraction to improve detection of small objects, which is critical in satellite imagery.

Advantages include:

- Real-time inference

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- High detection accuracy
- Lightweight deployment
- Strong transfer learning capability

VIII. SYSTEM-LEVEL SURVEILLANCE PIPELINE

A typical YOLOv8-based airbase surveillance system consists of:

1) Satellite image acquisition
2) Preprocessing and tiling
3) Aircraft detection using YOLOv8
4) Post-processing and counting
5) Visualization and reporting

IX. ALGORITHM

Airbase Surveillance using YOLOv8:

1) Input satellite image
2) Resize image to 640×640
3) Normalize pixel values
4) Apply data augmentation
5) Load pretrained YOLOv8 weights
6) Train model using annotated dataset
7) Perform inference on test image
8) Apply Non-Maximum Suppression
9) Count detected aircraft
10) Output annotated image and count

X. CHALLENGES

Major challenges in satellite-based aircraft detection include small object size, limited labeled datasets, sensor variability, occlusion and background clutter, and lack of multi-class labeling capability [1].

Despite significant advancements in deep learning-based detection, several technical and practical limitations remain unresolved. One of the most critical issues is the small-object problem [1]. In satellite imagery, aircraft often occupy only a few pixels, particularly in medium-resolution images. Limited spatial detail makes it difficult for neural networks to extract discriminative features, increasing the risk of missed detections and false negatives. Background complexity presents another major challenge [2]. Airbases contain visually similar structures such as hangars, runways, vehicles, storage tanks, and service equipment. Shadows, reflections, and runway markings frequently resemble aircraft shapes, leading to false positives and reduced precision.

Sensor variability and environmental conditions further affect detection performance [3]. Satellite images are captured under diverse lighting, seasonal, and atmospheric conditions. Cloud cover, haze, low illumination, and changes in sun angle alter object appearance, increasing intra-class variation and reducing model generalization. Dataset limitations remain a significant obstacle [4]. High-quality, large-scale aircraft datasets are scarce, and many studies rely on small or region-specific datasets. Models trained on limited data often struggle with cross-domain generalization when applied to new geographic regions or different satellite sensors. This domain shift problem significantly impacts real-world deployment.

Another key issue is annotation cost and labeling complexity [5]. Accurate bounding box annotation requires domain expertise and substantial manual effort. Inconsistent or noisy annotations degrade model learning and reduce detection reliability. Additionally, computational requirements pose practical challenges, as high-resolution satellite images demand powerful GPUs and optimized architectures for real-time processing.

Finally, most existing systems focus solely on object detection without integrating counting, visualization, alert generation, and scalable deployment mechanisms. The absence of unified surveillance frameworks limits operational usability and real-world defense application.

XI. COMPARATIVE ANALYSIS

Model	Speed	Accuracy
Faster R-CNN	Low	High
SSD	Medium	Medium
YOLOv5	High	High
YOLOv8	Very High	Very High

XII. APPLICATIONS

Applications of satellite-based aircraft detection span defense, civil, and humanitarian domains [1].

Major use cases include:

- Military airbase monitoring [1]
- Border surveillance
- Aircraft inventory tracking
- Disaster response [2]
- Search for missing aircraft
- Swarm drone surveillance [3]

Automated aircraft detection systems play a critical role in military and defense operations by enabling continuous monitoring of aircraft presence, movement, and deployment patterns [1]. Such systems support strategic planning, force assessment, and the early identification of unusual activity or sudden buildup of assets. Border security agencies can leverage these technologies to monitor nearby airfields and detect potential threats in real time.

In disaster management scenarios, automated detection assists in tracking rescue aircraft, helicopters, and transport fleets deployed for emergency response [2]. Monitoring airfield capacity and aircraft distribution improves coordination efficiency during relief operations. In civil aviation, satellite-based detection can support remote airport monitoring, runway utilization assessment, and air traffic analysis in areas lacking radar infrastructure.

Aircraft detection is also valuable for search- and-rescue missions, where deep learning models can help locate missing or crashed aircraft in remote, mountainous, or forested regions. Additionally, swarm drone surveillance systems integrated with lightweight detection models enable distributed monitoring and rapid area coverage [3]. Beyond operational deployment, aircraft datasets and detection frameworks contribute to research, training, and advancements in remote sensing and artificial intelligence.

XIII. FUTURE RESEARCH DIRECTIONS

Future work in aircraft detection and airbase surveillance can explore several promising directions [1].

Key research areas include:

- Multi-class aircraft detection [1]
- SAR and thermal imagery fusion [2]
- Edge-device optimization [3]
- Drone-based live monitoring
- Automated anomaly detection

Multi-class aircraft detection is an important extension of current systems. Distinguishing between fighter jets, transport aircraft, helicopters, and unmanned aerial vehicles would provide richer intelligence and enable more detailed

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force composition analysis [1]. Such classification capabilities would enhance situational awareness and strategic assessment.

Multi-sensor data fusion represents another significant research opportunity. Integrating optical imagery with Synthetic Aperture Radar (SAR), infrared, and thermal data can improve detection performance under adverse weather conditions, low illumination, or cloud cover [2]. Sensor fusion enhances robustness and reduces reliance on a single imaging modality. Transformer-based detection architectures also offer potential improvements in capturing global contextual information within large satellite images. Exploring these models for aircraft detection may further enhance localization accuracy and small-object recognition.

Edge computing and on-board drone processing can enable real-time aerial surveillance with reduced latency. Lightweight optimization strategies such as pruning, quantization, and knowledge distillation are essential for deploying detection models on resource-constrained devices [3]. Finally, integrating anomaly detection and behavior analysis frameworks can support automated identification of unusual aircraft activity, contributing to proactive and intelligent surveillance systems.

XIV. CONCLUSION

This review presented a comprehensive analysis of satellite image-based airbase surveillance using YOLOv8. Existing literature indicates that deep learning–based detection models, particularly modern YOLO architectures, provide a strong balance between detection accuracy and real-time performance [1]. Automated surveillance systems significantly enhance situational awareness and operational intelligence by enabling continuous monitoring of strategic airbases [2].

Although substantial progress has been achieved, challenges such as small-object detection, dataset diversity, cross-sensor generalization, and real-time deployment remain unresolved. Addressing these limitations is essential for building robust and scalable surveillance frameworks.

Overall, deep learning–driven airbase surveillance systems have the potential to transform defense monitoring by delivering accurate, scalable, and near real-time intelligence. Continued research and technological advancements will further improve the reliability, adaptability, and practical deployment of such systems across defense, civil, and humanitarian applications.

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