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Review Article

A Comprehensive Review for Aircraft Detection Techniques Utilizing Deep Learning

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Abstract
Aircraft detection is a vital and significant field within object detection that has garnered considerable attention from academics, particularly following the advancement of deep learning methods. Aircraft detection has recently become widely utilized in several civil and military fields. This comprehensive survey meticulously categorizes and evaluates diverse deep learning methodologies in airplane detection research. Encompassing radar-based, image-based, and multimodal approaches, the paper presents a structured framework to enhance understanding of the evolving research landscape within this domain. The survey critically identifies gaps and discerns emerging trends, offering valuable insights into standard datasets of aircraft images, performance metrics, real-world applications, and challenges and limitations encountered by aircraft detection systems. Its potential contributions are underscored as pivotal for advancing the safety and security of air travel. This research paper is the inaugural publication of its kind in the domain of aircraft detection review papers, establishing itself as an all-encompassing reference for subsequent scholars.

Keywords
Deep Learning, Aircraft Detection, Two-stage Approach, One-stage Approach.

I. Introduction

Object detection stands as a main stone in the domains of computer vision, deep learning, and artificial intelligence, playing a pivotal role in advanced tasks like target tracking, event detection, behavior analysis, and semantic scene understanding. The primary aim of object detection is to precisely identify object targets within an image, accurately classify their categories, and provide bounding box coordinates for each detected target [1]. This capability holds significant importance in both scientific research and practical industrial applications, finding use in diverse fields such as face detection, text detection, pedestrian detection, video analysis, medical image analysis, and the detection of vehicles like cars, ships, and aircraft [2, 3].

Detecting aircraft poses unique challenges that set it apart from general object detection. These challenges, for example, in remote sensing images, encompass factors like variations in scale, complex backgrounds, and diverse shapes [4], necessitating specialized algorithms to discern specific features associated with aircraft. This specialization makes aircraft detection a distinct subset within the broader field of object detection. Furthermore, the complexities in aircraft detection extend to considerations of movement, the analysis of Synthetic Aperture Radar (SAR) images, and challenges related to autonomous navigation. Addressing these complexities requires focused attention and customized approaches to accommodate dynamic flight patterns, diverse environmental conditions captured in SAR imagery, and the intricacies associated with the autonomous behavior of aircraft in different operational scenarios.

The focal point of the paper includes the following key contributions:

1. This review paper undertakes a comprehensive exploration of deep learning approaches specifically designed for aircraft detection.

2. Highlighting ongoing research efforts that leverage radar technology, computer vision, and multimodal sensing. Emphasizing the goal of developing detection systems capable of handling the intricacies associated with aircraft detection.

3. In essence, this survey paper serves as a valuable resource for comprehensively reviewing state-of-the-art methodologies in airplane detection, offering insights into the challenges faced and the advancements made in addressing them.

4. Discusses the integral role of airplane detection in domains like air traffic control, military surveillance, and aerial reconnaissance. Recognizes its importance in addressing the growing demands on airspace utilization and heightened security concerns.

II. Background

Aircraft detection stands as a critical aspect in various domains, including air traffic control, military surveillance, and aerial reconnaissance, given the escalating demands on airspace utilization and heightened security concerns [5,6]. Researchers are making efforts to develop and explore innovative approaches to enhance detection systems, addressing the complexities inherent in identifying aircraft. As airspace utilization demands grow and security concerns heighten, the effective detection of airplanes becomes increasingly crucial, driving advancements and ongoing research in the field.

After a comprehensive investigation, it was discovered that there is only one existing review paper [7] specifically addressing aircraft detection. Consequently, the inclusion of prior works related to review papers on aircraft detection in this review is not feasible. As a result, our focus shifts to presenting relevant research on object detection as a broader field, which has been extensively covered by scholars in recent years. Despite this limitation, Table I in this review encapsulates related work conducted within the past three years and the current year, offering a glimpse into the latest developments in the object detection field.

Many researchers have made substantial contributions to object detection in recent years, focusing on using cutting-edge deep learning algorithms, as Table I illustrates. The prevailing trend in contemporary surveys on object detection revolves around highlighting advancements in the broader domain of object detection facilitated by deep learning.

To accomplish this objective, these surveys establish a systematic framework of categories for object detection techniques. They meticulously examine fundamental techniques that have exerted significant influence, providing a comprehensive landscape overview. Moreover, these surveys delve into discussions on widely used datasets and evaluation measures, thereby contributing to a thorough understanding of the subject [8].

III. The General Architecture of Object Detection

Aircraft detection, a specialized form of object detection, is dedicated to identifying and locating aircraft within an image. The primary goal is pinpointing all instances of predefined categories in the image by employing axis-aligned boxes. The detector is tasked with accurately detecting and classifying all occurrences of object classes and precisely outlining a bounding box around each instance. Recent object detection models rely on massive datasets comprising labeled images for training and evaluation. These models are systematically assessed on established benchmarks, employing sophisticated deep learning techniques to enhance their performance [9].

After a comprehensive review of various studies within the field of aircraft detection employing deep learning, as indicated by [10–14] a clear pattern emerges regarding the fundamental architecture of the aircraft detection model, which comprises five pivotal stages. The process initiates with the compilation of a dataset containing images specifically focused on aircraft. Subsequently, the stages involve data preprocessing, feature extraction, the implementation of an adept deep learning detector, and the subsequent evaluation of the detection outcomes.

An aircraft dataset is a systematically organized collection of images with a specific focus on aircraft, curated for diverse applications within the realms of computer vision and machine learning. These datasets play a pivotal role as valuable assets for training, testing, and validating algorithms and models engineered to analyze and interpret visual data. Covering an array of categories and conditions relevant to the targeted application or research field, these datasets contribute significantly to the development and evaluation of robust models. The quality and quantity of the dataset hold substantial influence over the efficacy of detection models. Furthermore, these datasets are essential for assessing and verifying the accuracy of proposed methodologies [15]. Establishing a solid foundation for training and evaluation, standard datasets such as the Dataset of Object Detection in Aerial Images (DOTA) [16] and Remote Sensing Object Detection (RSOD) [17], are widely employed in this domain.

Preprocessing plays a crucial role in preparing aircraft images for subsequent stages [18]. The raw images in the dataset cannot be directly processed by the detection system, necessitating essential adjustments to image dimensions and

improvements to clarity by refining aspects like brightness, color, and contrast. Data augmentation, a vital component, involves operations such as rotation, scaling, cropping, and noise deletion to meet specific requirements [24]. This phase ensures that the input data undergoes appropriate transformations, enriching it to optimize the performance of subsequent stages in the image processing pipeline.

In the feature extraction phase, deep learning filtering is employed to extract and filter out irrelevant features [25, 26]. These features are then fed into the detection phase to accurately identify airplanes.

The detection phase consists of two integral tasks: localization and classification [9]. In the localization task, the objective is to precisely determine the aircraft's position by defining a bounding box around it. Concurrently, the classification task focuses on categorizing the detected object, specifically identifying it as an aircraft [12]. To enhance the accuracy and efficiency of aircraft detection, recent advancements have embraced sophisticated deep-learning detectors such as Region-based Convolutional Neural Networks (RCNN) and You Only Look Once (YOLO) [27]. These cutting-edge models contribute to achieving both precision and speed in the detection process. The ultimate outcome of this phase involves encapsulating the identified aircraft within a bounding box within the image, definitively confirming its classification as an aircraft [28].

The final stage involves evaluating the system's performance by assessing the obtained results using different evaluation metrics such as accuracy, mean Average Precision (mAP), and F1-score. Fig. 1 Illustrate the general framework of object detection as well as aircraft detection .

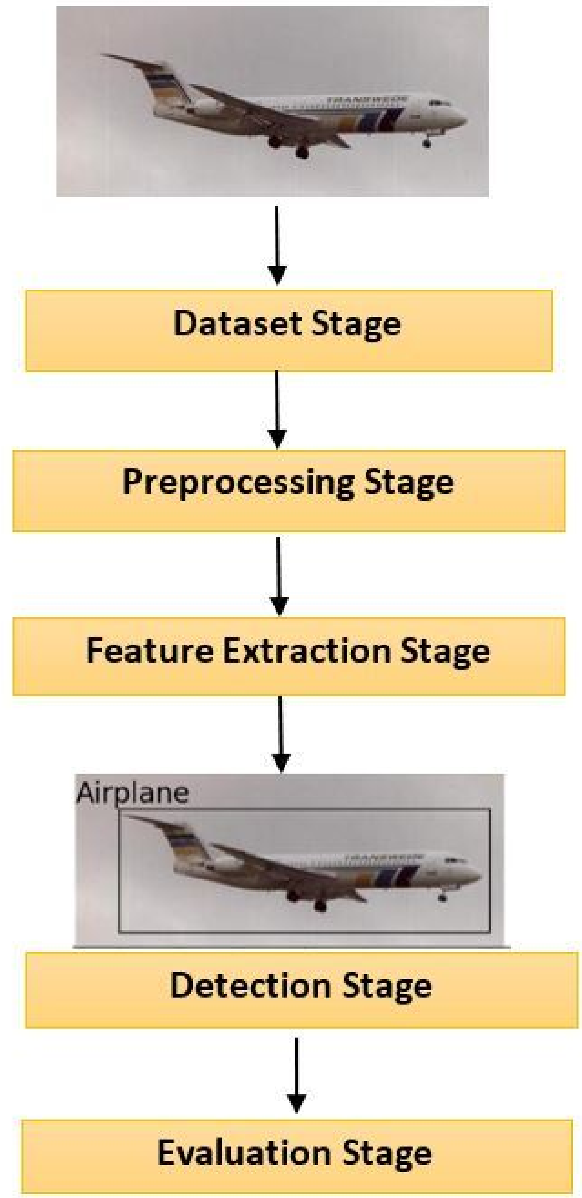

Fig. 1. General Framework of Object Detection

IV. Taxonomy of Detection Approaches

The taxonomy of approaches in aircraft detection encapsulates a comprehensive categorization of methodologies employed in identifying and localizing aircraft. This classification is essential for understanding the diverse strategies and technologies utilized in the field. The taxonomy typically comprises three main categories: sensor-based detection, featuring techniques reliant on specific sensor modalities such as radar, LIDAR, and infrared; image-based detection, which focuses on leveraging visual information through optical and satellite imagery; and multi-sensor fusion, integrating data from multiple sources for enhanced accuracy and robustness. Within each category, specific techniques may include deep learning-based methods, traditional machine learning algorithms, and hybrid models.

A. *Sensor-based Detection*

Sensor-based taxonomy plays a pivotal role in categorizing aircraft detection methodologies based on the type of sensors utilized, contributing to a nuanced understanding of detection approaches. This taxonomy encompasses various sensor modalities, each offering distinct advantages and challenges [29]. The primary categories within the sensor-based taxonomy include Radar-Based Detection, Lidar-Based Detection, and Infrared-Based Detection [30].

TABLE I.
SUMMARY OF RELATED SURVEYS ON OBJECT DETECTION IN THE LAST FOUR YEARS

References	Survey Title	Year	Advantage	Disadvantage
[9]	A Survey of Modern Deep Learning based Object Detection Models	2021	This survey examines the latest progress in object detectors that utilize deep learning techniques	This research omitted crucial aspects of object detection, including: Lightweight detectors, 3D object detection, and object detection in video
[19]	Deep Learning for Object Detection: A Survey	2021	This article investigated the latest progress in object detection and provided a concise introduction to the literature studies	This survey does not include a thorough analysis of object detection in video or the detection of small objects
[20]	Deep Learning-Based Object Detection Techniques for Remote Sensing Images: A Survey	2022	This paper examined the latest developments in remote sensing object detection systems, encompassing both traditional and deep learning methodologies	This research needs to address many problems related to remote sensing object detection, such as: improve weakly supervised learning, improve small object issues
[21]	Object Detection in 20 Years: A Survey	2023	This study provided a comprehensive analysis of the rapidly evolving research field, taking into account technological advancements over twenty-five years (from the 1990s to 2022)	This study does not include a thorough analysis of many aspects such as: object detection in video or the detection of small objects
[22]	A Comprehensive Review of Object Detection with Deep Learning	2023	In this review, object detection and its different aspects have been covered in detail, such as: object detection framework, object detection problems and applications	This review does not include a thorough analysis of many aspects such as: object detection in video or the detection of small objects
[23]	Remote Sensing Object Detection in the Deep Learning Era—A Review	2024	This study presents an overview of the advancements in object detection methods and their closely related technique, instance segmentation, in the era of deep learning. Its purpose is to give researchers up-to-date information on these topics	This research does not sufficiently address the problems and challenges that influence remote sensing object detection

1) Radar-based Detection

Radar-based detection is a pivotal component in the realm of aircraft detection, offering a robust and versatile approach to identifying and tracking airborne objects. This technique relies on the use of radar systems, leveraging radio frequency signals to detect the presence, location, and motion characteristics of aircraft. Radar-based detection is particularly advantageous due to its capability to operate in various environmental conditions, including adverse weather and low visibility scenarios [30, 31].

The fundamental principle involves emitting radio waves, which, upon encountering an aircraft, undergo reflection and are subsequently detected by the radar receiver. The resulting signals are then processed to extract relevant information such as the aircraft's range, speed, and heading [30, 31]. Radar-based detection systems have demonstrated effectiveness in both military and civilian applications, contributing significantly to air traffic control, surveillance, and defense mechanisms [32, 33]. While radar-based approaches have long been established, ongoing research aims to enhance their capabilities through integration with advanced technologies such as deep learning, thereby further improving accuracy and adaptability in diverse operational contexts.

2) LIDAR-based Detection

LIDAR-based detection stands at the forefront of cutting-edge technologies for aircraft detection, relying on Light Detection and Ranging (Lidar) systems to capture detailed and accurate information about the surrounding airspace [34]. LIDAR operates by producing laser pulses and calculating the duration it takes for the light that is reflected to come back, allowing for the generation of detailed, three-dimensional maps of the environment [30]. In aircraft detection, LIDAR is useful in precisely detecting and characterizing aircraft.

The technology offers advantages such as fine spatial resolution, the ability to discern object shapes, and efficacy in various lighting conditions. LIDAR-based detection finds applications in autonomous driving, aviation safety, autonomous navigation, and environmental monitoring [20]. Current research efforts are focused on improving LIDAR systems by advancing sensor technology and data processing techniques. This will lead to better accuracy and reliability in detecting airplanes. The integration of LIDAR with complementary technologies, including machine learning and deep learning, further contributes to the evolution of robust and efficient aircraft detection systems.

3) Infrared-Based Detection

Infrared-based detection exploits the thermal radiation emitted by objects, including airplanes, to identify and locate them. Infrared sensors detect the heat signatures of airplanes, making this approach particularly advantageous in low-light or nighttime conditions. Infrared-based detection is less affected by visual obscurants like fog and can contribute to 24/7 surveillance capabilities. It is commonly employed in conjunction with other sensor modalities for comprehensive coverage [35, 36].

B. Image-based Detection

Image-based detection stands as a pivotal domain within aircraft detection methodologies, leveraging visual data to identify and locate airborne objects [37]. In this approach, the analysis is primarily rooted in the information extracted from images, encompassing both optical and satellite imagery [38].

The image-based detection process involves the utilization of computer vision techniques, pattern recognition, and deep learning algorithms to discern aircraft from their surroundings [38]. These methods often rely on datasets comprising aerial images captured under diverse conditions, contributing to the training and evaluation of detection models. Image-based detection is integral in various applications, including surveillance, border control, and military operations [39, 40].

The advancements in high-resolution imaging technologies, coupled with sophisticated image processing algorithms, continue to refine the precision and competence of aircraft detection. Ongoing research in this field aims to address challenges such as occlusion, scale variations, and diverse environmental conditions, paving the way for increasingly robust image-based aircraft detection systems [4]. In this paper, the focus will be on satellite images-based detection.

Satellite image-based detection is a pivotal category within sensor-based approaches for aircraft detection, leveraging Earth-observation satellites equipped with diverse sensors. These satellites capture high-resolution imagery from space, offering a comprehensive and expansive perspective for monitoring and identifying aircraft activities [38]. The data collected from satellite sensors, including Optical remote sensing images (RSIs) and Synthetic Aperture Radar (SAR), contributes to the precise detection, tracking, and analysis of airplanes across varied geographical locations.

1) Optical Remote Sensing Images

Optical remote sensing images a prominent category within sensor-based approaches for aircraft detection, relying on the utilization of visual information captured by optical sensors, such as cameras, to identify and locate airplanes. This methodology leverages the rich visual data inherent in optical images, enabling detailed analysis of the aircraft's appearance, shape, and contextual information.

Optical image-based detection has witnessed significant advancements with the integration of deep learning techniques, particularly Convolutional Neural Networks (CNNs), for robust feature extraction and recognition Remote Sensing Images (RSIs) are an example of optical images that are produced by capturing data about a target object by detecting reflected, radiated, or scattered electromagnetic waves. This data are collected by sensors deployed on remote platforms significantly from the target object [41]. RSI can accurately depict the shape, size, color, and other characteristics of the target surface and can be used for feature observation and recognition. Since remote sensing images from satellite sensors are taken from high altitudes and include atmospheric interference, viewpoint fluctuation, background clutter, and lighting variances, they are far more complex than computer vision images.

Furthermore, compared to digital photographs produced by cameras, satellite images cover wider regions (at least 10

Fig. 2. RSI Image

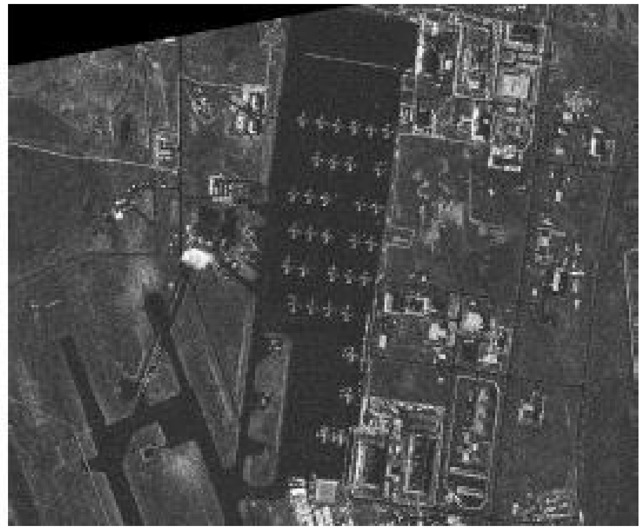

Fig. 3. SAR image

km x10 km for one image frame) and reflect the complex terrain of the Earth's surface (various land types) with two-dimensional images with less spatial resolution [10, 42]. Remote sensing images exhibit diverse scales, directions, small objects, and complicated backgrounds. However, they share common object features with natural images, including low-level semantic features like edges and colors, as well as abstraction of high-level semantic features [43]. Lately, detecting aircraft in remote sensing data has gained significant attention in many fields, including environmental monitoring, military operations, and civil applications [25, 39]. See fig. 2 [44].

2) Synthetic Aperture Radar (SAR) Images

Comprehensive depiction of the Earth's surface, obtained using SAR, a specialized radar technology [45]. It possesses the unique capability of being unaffected by atmospheric conditions like as clouds and fog, enabling it to capture images of the surface of the Earth continuously, regardless of the time of day [46, 47]. Synthetic Aperture Radar (SAR) can produce detailed high-resolution images regardless of the time of day, weather conditions, or lighting circumstances. This characteristic confers distinct advantages upon SAR compared to alternative sensors like optical, infrared, and hyperspectral sensors [48].

In recent years, Synthetic Aperture Radar (SAR) satellites have increased, including Sentinel-1, TerraSAR-X, and Chinese Gaofen-3. As a result, there has been a significant increase in the availability of high-resolution SAR imagery for the purpose of scientific research [49]. Synthetic aperture radar (SAR) is a highly utilized technology across numerous domains because it offers uninterrupted and consistent monitoring throughout both day and night. The rapid advancement of synthetic aperture radar (SAR) technology has facilitated the acquisition of a substantial amount of high-resolution data from both spaceborne and airborne platforms. This influx of data presents novel prospects for detecting targets using SAR [50]. See fig. 3 [51].

The increasing resolution of acquired Synthetic Aperture Radar (SAR) images has led to a growing adoption of aircraft detection in advanced imagery analysis research. The detection of aircraft is a significant problem due to factors such as the escalating amount of data, intricate backgrounds, and the dispersed nature of aircraft image characteristics as detection targets [13, 50]. The efficacy of traditional SAR image target detection techniques has seen certain advancements; nonetheless, these methods necessitate prior information and exhibit a need for more robustness. Moreover, the actual applicability of these algorithms is limited by their detection timeframes [52, 53].

In recent years, the field of detecting aircrafts has witnessed widespread use of advanced deep learning models due to the rapid progress in deep learning technologies. Convolutional neural networks (CNNs) possess robust feature extraction capabilities through their end-to-end architectures, rendering them the prevailing deep learning methods for target detection. Consequently, they present significant prospects for detecting aircraft in synthetic aperture radar (SAR) images [50, 54]. See fig 4. More details about the topic at the next section.

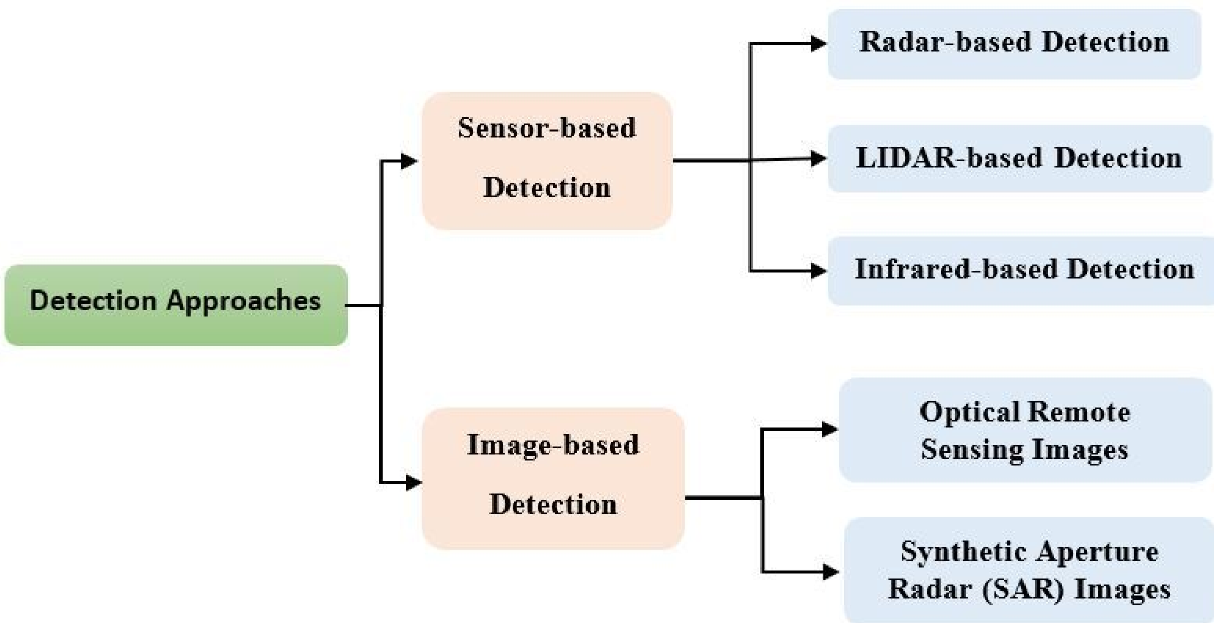

Fig. 4. Taxonomy of Detection Approaches

V. Deep Learning-based Approaches

Due to advancements in high-performance hardware, deep learning has become extensively researched and implemented in computer vision domains, including classification, semantic segmentation, and, detection [55]. Deep neural networks have the capability to extract highly abstract semantic information, hence enhancing the representation capacity of features and significantly improving the accuracy and speed of object detection [43].

The convolutional neural network (CNN) is an essential architecture in the field of deep learning due to its robust feature description capabilities. It has achieved significant advancements in various domains. CNN-based object detection approaches eliminate the requirement for human feature design. Traditional detection methods are surpassed by their superior detection accuracy and generalization capabilities [46].

Target detection techniques based on Convolutional Neural Networks (CNN) in general and aircraft in particular can be classified into two distinct groups: One type of target detection algorithm is region-based, which is used in two-stage algorithms like Region-based Convolutional Neural Network (R-CNN) and Fast Region-based Convolutional Neural Network (Fast R-CNN). These algorithms exhibit a high level of accuracy in their detecting capabilities, but their pace could be faster. The second group consists of the regression-based detection of targets technique, encompassing the one-stage methods referred to as You Only Look Once (YOLO) and SSD (Single Shot multi-box Detector). This method converts the task of detection into a task of regression, resulting in a substantial increase in speed [56].

A. Two-stage Approaches

A two-stage detector is a network that includes a distinct module for generating region proposals. These approaches aim to identify a variable number of item proposals in an image within the initial stage and subsequently classify and locate them in the second stage using category-specific classifiers to determine the category labels of the proposals. Due to the presence of two distinct stages, these systems typically require more time to create proposals, possess intricate designs, and lack a global context [9, 57]. R-CNN, Faster R-CNN and Spatial Pyramid Pooling in Deep Convolutional Network (SPPNet) are the most famous examples of two-stage detectors. Fig. 5 [58] illustrates the Inside design of two-stage object detectors.

Recently many researchers have been proposed various aircraft detection methods in context of two-stage deep learning:

Chen et al. introduced an innovative framework for detecting aircraft targets. They developed a region proposal approach that utilized a circular intensity filter to accurately identify probable aircraft targets at various scales in RSIs images. Furthermore, the researchers utilized the VLAD method to encode the rotation-invariant Fourier HOG feature. This approach exhibits fewer dimensions and offers a more resilient depiction of the target's rotational movement. The optical remote sensing images were acquired from the RSOD dataset, consisting of 446 images capturing an overall of 4993 aircraft objects. The images have dimensions of 1072 × 975 pixels and 1116 × 659 pixels. The photos were sourced from Google Earth and Tianditu, both of which offer spatial resolutions ranging from 0.5 m to 2 m. The results showed that the proposed method could quickly and accurately detect aircraft targets in RSIs and achieve a better performance. The average precision was 93.4%, and this was higher than the precision values of other methods [44].

Qiangwei et al. developed an aircraft detection method that utilizes corner clustering and Convolutional Neural Network (CNN). The scheme consisted of two primary stages: region suggestion and classification. Initially, candidate regions are produced by applying the mean-shift clustering technique to the corners identified on binary pictures. Subsequently, the Convolutional Neural Network (CNN) was employed to extract distinctive features and classify potential areas that may contain the aircraft. The precise location of the aircraft was ultimately ascertained through subsequent scrutiny. The optical remote sensing pictures utilized were sourced from the RSOD dataset. The collection has 446 photos of aircraft, 4993 aircraft in total. The image dimensions are 1072 × 975 pixels and 1116 × 659 pixels. The final model achieved a classification accuracy (AC) of 98.29% after thorough testing [25].

Luo et al. introduced a novel eXplainable Artificial Intelligence (XAI) framework for transparently analyzing Deep Neural Networks (DNN) by employing airplane detection as a specific example. The architecture consisted of three components: Hybrid Global Attribution Mapping (HGAM) for selecting the backbone network, PAth aggregation Network (PANet), and Class-specific Confidence Scores Mapping (CCSM) for visualizing the detector. The study utilized a dataset consisting of 15 high-resolution SAR images captured by the Gaofen-3 system. These images depicted several airports and had a resolution of 1 meter. After SAR professionals personally recognized and confirmed the aircraft, the SAR images were separated into 512 × 512 pixel samples using an automated process. The evaluation metrics were Precision (P) = 91.63%, Recall (R) = 93.25%, mean Average Precision (mAP) = 91.58% [13].

Zhang et al. proposed a novel approach to detect airplanes in SAR images with a low Signal-to-Clutter-Noise Ratio (SCNR). This strategy employed coherent scattering enhancement and a fusion attention mechanism. In addition, it enhanced the Faster R-CNN model by integrating a unique pyramid network that includes features for both local and contextual attention. The contextual attention mechanism allows the network to retrieve relevant contextual information from the image, whereas the local attention mechanism selectively highlights essential elements by boosting their distinctive qualities. The network can detect aircraft by efficiently incorporating local and contextual attention. Much experimentation was conducted using the Terra SAR-X SAR datasets to develop benchmarks. The experimental results demonstrate that when the SCNR is low, the proposed aircraft detection approach achieved an average precision of 91.7% [59].

Khalaf et al. presented a method for detecting airplanes, irrespective of their model, kind, or color variations. Object detection can be accomplished by dividing the process into three main stages: feature extraction, airplane detection, and evaluation of the detected airplane. A deep feature extraction method utilizing the VGG model is employed to extract the plane region. The aircraft was identified using Support Vector Machines (SVM). The effectiveness of the designed system is evaluated using two datasets: Caltech-101 and FGVC-Aircraft dataset. The results demonstrated a 99% F1-score when using the Caltech-101 dataset and 98% when using the FGVC-Aircraft dataset [60].

Table II summarizes the above-mentioned related works.

B. One-stage Approaches

A one-stage detector is a network that uses a single feed-forward CNN to directly predict class probabilities and bounding box offsets from whole images. These architectures do not involve region proposal generation or post-classification/feature resampling. All computation is encapsulated in a single network [57]. It outperforms two-stage detectors in terms of real-time performance and has a more streamlined architecture [9]. You Only Look Once (YOLO) and SSD (Single Shot multi-box Detector) are the most famous examples of one-stage detectors. Fig. 5 [58] shows the inside design of one-stage detectors.

Many researchers have recently suggested different aircraft detection techniques in the framework of one-stage deep learning:

Luo et al. introduced the Efficient Bidirectional Path Aggregation Attention Network (EBPA2N). The EBPA2N framework utilized YOLOv5s as the foundational network. Subsequently, the Involution Enhanced Path Aggregation (IEPA) module and the Effective Residual Shuffle Attention (ERSA) module were introduced and seamlessly incorporated to enhance the precision of aircraft identification. Three

TABLE II.
SUMMARY OF RELATED WORK OF TWO-STAGE AIRCRAFT DETECTORS

References	Published year	Dataset	Image type	Image size (in pixels)	Deep learning aircraft detector	Experimental results
[13]	2021	Gaofen-3	SAR	512 × 512	XAI framework	P= 91.63% R = 93.25% mAP = 91.58%
[25]	2020	RSOD	RSI	1072 × 975 and 1116 × 659	CNN	A C = 98.29%
[44]	2022	RSOD	RSI	1072 × 975 and 1116 × 659	Fourier HOG Feature and VLAD	AP = 93.4%
[59]	2023	Terra SAR-X	SAR	256 × 256	Faster R-CNN	AP = 91.7%
[60]	2024	Caltech-101, FGVC-Aircraft dataset	Real-World Images	300 × 200	VGG and SVM	F1-score = 99% F1-score = 98%

high-quality SAR images with a 1-meter resolution from the Gaofen-3 system are used for independent testing. The images represent three different airports: Hongqiao Airport (Airport I) with dimensions of 12,000 × 14,400 pixels, Capital Airport (Airport II) with dimensions of 14,400 × 16,800 pixels, and Military Airport (Airport III) with dimensions of 9,600 × 9,600 pixels. The EBPA2N algorithm exhibited a detection rate of 93.05% and a false alarm rate of 4.49%, surpassing the performance of the current EfficientDet-D0 and YOLOv5s networks. Additionally, it has the advantage of faster detection speed [50].

Li et al. proposed a lightweight detection model (LDM) that consists mainly of a reused block (RB) and an information correction block (ICB) built upon the Yolov3 framework. The RB module facilitated the neural network in extracting comprehensive airplane characteristics by consolidating multilayer information. Although the RB module enhanced the effectiveness of the information, it also accumulated redundant and irrelevant data through the reuse block, so compromising the accuracy of detection. A sequence of tests was carried out on the SAR aircraft detection dataset (SAR-ADD). The Average precision (AP) established a superiority over the accuracy values attained by other approaches, with a value of 69.54% [52].

Zhao et al. introduced a novel detection model called Attentional Feature Refinement and Alignment Network (AFRAN) for accurately and efficiently detecting airplanes in SAR images. The method meticulously incorporates three key components: The Attention Feature Fusion Module (AFFM), the Deformable Lateral Connection Module (DLCM), and the Anchor Guided Detection Module (ADM). These components are designed to refine and align the informative properties of aircraft. In order to evaluate the detection performance of the system, a self-built dataset of sliced aircraft images and a big scene SAR image was collected, as there was no publicly available dataset for aircraft detection in SAR images. The evaluation metrics were Precision = 90.4% Recall = 93.2% , F1 score= 91.8% [54].

Wang et al. presented a highly efficient remote sensing aircraft object detection network based on the enhanced YOLOv5n. This network integrates the Shufflenet v2 and YOLOv5n models, substantially reducing network size without compromising detection accuracy. The original CIoU and convolution are replaced with EIoU and deformable convolution, which focuses on optimizing for the specific features of small-scale aircraft objects. This substitution leads to faster convergence and improved accuracy in regression. Furthermore, a coordinate attention (CA) mechanism is implemented after the main structure to target orientation perception and positioning information specifically. The experimental findings obtained from the Mar20 public dataset demonstrate that the suggested network attained a mean average precision (mAP) of 95.2% [61].

Chen et al. introduced the You Only Look Once-SAR Aircraft Detector (YOLO-SAD), which utilizes the Attention-Efficient Layer Aggregation Network-Head (A-ELAN-H) module to prioritize crucial features for enhanced precision. The SAR Aircraft Detection-Feature Pyramid Network (SAD-

FPN) enhances the fusion of multi-scale features, resulting in improved detection speed. Enhanced Non-Maximum Suppression (EH-NMS) effectively removes overlapping detections. YOLO-SAD attained an average precision (AP) of 91.9% on the SAR Aircraft Detection Dataset (SADD) [62].

Table III summarizes the above-mentioned related works and fig. 6 shows the taxonomy of artificial intelligence and deep learning.

VI. Datasets For Aircraft Detection

Datasets serve as pivotal components in the training and evaluation of aircraft detection models, contributing significantly to the progression of aircraft detection research. Throughout the evolution of aircraft detection, datasets have not only provided a standardized benchmark for assessing and comparing algorithmic performance but have also propelled the field towards addressing increasingly intricate and challenging problems [57].

In recent years, a collection of datasets has been curated explicitly for aircraft detection, encompassing the identification of aircraft in RSI and SAR images. Noteworthy datasets in this domain include DOTA and RSOD, among others. The ensuing section delves into a more detailed elucidation of some of the predominant datasets, shedding light on their characteristics and contributions to advancing the capabilities of aircraft detection algorithms.

A. Caltech-101

The Caltech-101 dataset [63] holds a prominent position in the realm of computer vision, serving as a widely utilized resource for object recognition and classification endeavors. Developed by the California Institute of Technology, this dataset encompasses a rich collection of approximately 9,146 images spanning 101 distinct object categories [26]. Each category presents a variable number of images, ranging from 40 to 800, and the dataset is carefully crafted to introduce challenges related to scale, viewpoint, and lighting conditions [64]. The primary objective of Caltech-101 is to establish a rigorous benchmark for evaluating the efficacy of object recognition algorithms. The dataset includes 800 aircraft images, and the uniform dimension of the images is set at 300 x 200 pixels. It adds consistency to the dataset, contributing to its widespread adoption in the evaluation and advancement of computer vision models. Fig. 7 shows some samples of images for Caltech-101 dataset.

B. UC Merced Land (UCM)

The UCM dataset [65] comprises 21 distinct categories, with each category containing a total of 100 images. The images were hand-chosen from huge images acquired from the USGS National Map Urban Area Imagery collection for different urban regions around the United States. The UC Merced dataset consists of 2100 images in total, each with dimensions of 256 × 256 pixels containing three channels of a pixel resolution of one foot [42, 66], It is noteworthy that the UCM dataset includes a diverse range of spatial land-use patterns, which adds complexity to the dataset. Furthermore, the presence of highly overlapping classes, such as dense residential, medium residential, and sparse residential, which primarily vary in the density of structures, poses a challenge for classifying the dataset. The collection is extensively utilized for the purpose of aerial picture classification [67].

C. Unmanned aerial vehicle Car Detection and Aircraft Object Detection (UCAS-AOD)

The UCAS-AOD dataset [68] is intricately designed for the specific task of object detection in aerial images, with a particular emphasis on unmanned aerial vehicle (UAV) surveillance contexts. The dataset captures images under diverse and challenging conditions, providing a nuanced representation of scenarios crucial for training and evaluating object detection algorithms. Notably, it encompasses instances of both cars and aircraft, accompanied by annotations that facilitate the nuanced development and assessment of detection models. The primary aim of the UCAS-AOD dataset is to propel the advancement of accurate and resilient object detection algorithms, with a special focus on the complexities inherent in UAV surveillance and aerial imagery.This dataset serves as a valuable resource for researchers and practitioners, offering the potential to augment the capabilities of object detection systems in real-world applications. In addition, UCAS-AOD specifically includes a subset of the aerial image dataset obtained from Google Earth containing aircraft data, consisting of 600 images that collectively feature 3210 occurrences of aircraft, each with an image resolution of approximately 1000 × 1000 pixels [20, 69].

D. NorthWestern Polytechnical University Very High-Resolution-10 (NWPU VHR-10)

The NWPU VHR-10 dataset [69], a prominently utilized remote sensing detection dataset in recent years, comprises 800 high-resolution images extracted from satellites, sourced from Google Earth and Vaihingen datasets [4]. These images encapsulate ten categories of prevalent items, including aircraft, ships, harbors, and bridges [20, 69].

Specifically focusing on aircraft, the NWPU VHR-10 collection incorporates 90 images, totaling 757 instances and 664 aircraft. The image dimensions vary, with widths of 958 and 1025 pixels, and heights of 808 and 578 pixels, respectively [25]. NWPU VHR-10, designed for very high-resolution object detection, features images annotated at the

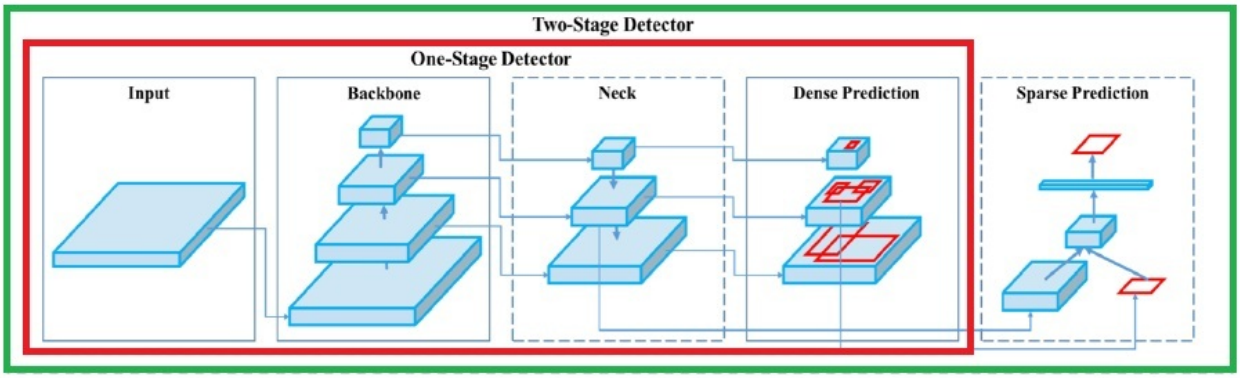

Fig. 5. A Graph Illustrates the Inside Design of One-stage and Two-stage Object Detectors

TABLE III.
SUMMARY OF RELATED WORK OF ONE-STAGE AIRCRAFT DETECTORS

References	Published year	Dataset	Image type	Image size (in pixels)	Deep learning aircraft detector	Experimental results
[50]	2021	Gaofen-3 satellite system	SAR	512 × 512	EBPA2N, YOLOv5s	AC = 93.05%
[52]	2021	SAR-ADD dataset	SAR	500 × 500	Lightweight Detection Model (LDM)	AP = 69.54%
[54]	2022	Self-built aircraft sliced dataset	SAR	Varied	Attentional Feature Refinement and Alignment Network(AFRAN)	P = 90.4% R = 93.2% F1-score = 91.8%
[61]	2024	Mar20 public dataset	RSI	640 × 640	YOLOv5n and Shufflenet v2	mAP= 95.2%
[62]	2024	SADD	SAR	224 × 224	YOLO-SAD	AP = 91.9%

pixel level, allowing for detailed analysis of detection models. Its significance lies in advancing the precision and accuracy of object detection algorithms, particularly in scenarios requiring high-resolution imagery and meticulous object delineation.

E. Remote Sensing Object Detection (RSOD)

The RSOD dataset [17] is intricately designed for object detection within Remote Sensing images (RSIs), featuring a total of 976 images across four distinct groups: airplane, overpass, playground, and oil drum [4]. Comprising 446 remote sensing images, RSOD provides a comprehensive set of 4993 annotated aircraft targets, with image dimensions varying between 1072 × 975 and 1116 × 659. Sourced from platforms such as Google Earth and Tianditu, the images exhibit spatial resolutions ranging from 0.5 m to 2 m [44, 69].

Tailored for remote sensing object detection, RSOD holds particular relevance for aircraft detection in satellite images, encompassing diverse objects, including aircraft and ships. The dataset's detailed annotations, specifying object boundaries, contribute to the precision of training and evaluating detection algorithms. RSOD's emphasis on remote sensing scenarios augments the development of models adept at identifying and localizing aircraft within intricate and dynamic environmental contexts. Fig. 8 [70] shows some samples of images for RSOD dataset.

F. NorthWestern Polytechnical University-REmote Sensing Image Scene Classification45 (NWPU-RESISC45)

The NWPU-RESISC45 dataset [71] is a large-sized dataset comprises a total of 31,500 images, which are categorized

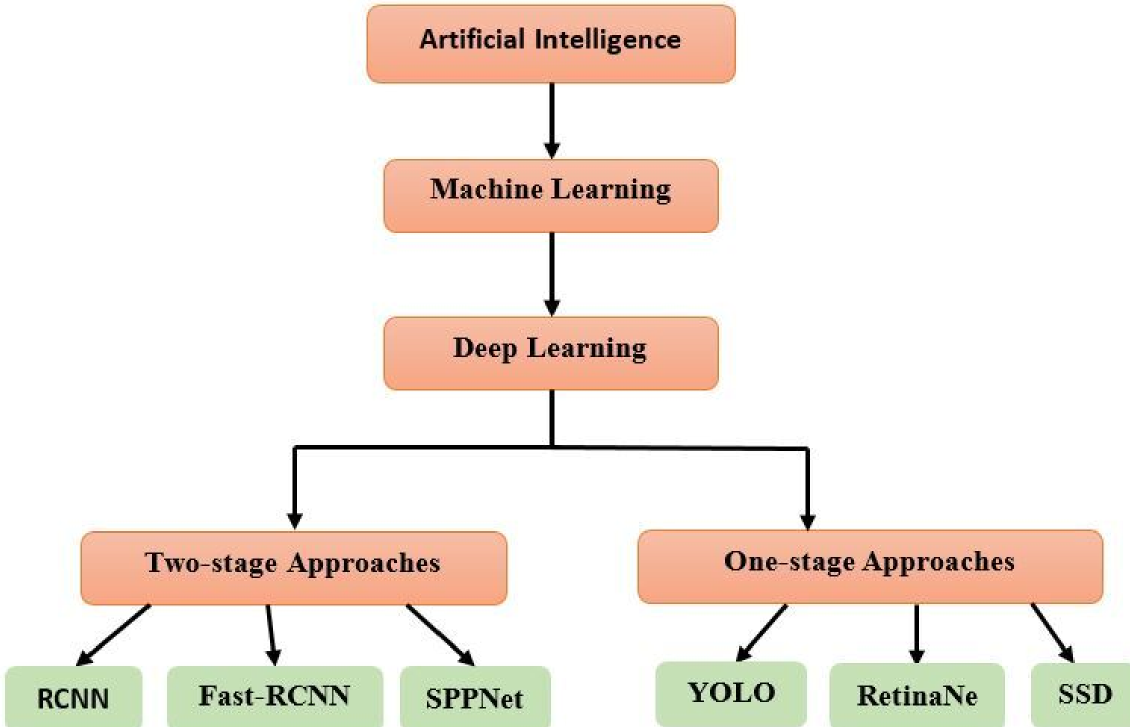

Fig. 6. A Graph Illustrates the Taxonomy of Artificail Intelligence and Deep Learning

Fig. 7. Sample Images from Caltech-101 Dataset

into 45 distinct classes. Every class comprises a total of 700 images within the RGB color space. The spatial resolution of these photos varies from 0.2 m to 30 m. Since its publication in 2017, this dataset has been extensively utilized for scene classification [42, 72].

Fig. 8. Sample Images from RSOD Dataset

G. Aerial Image Dataset (AID)

The AID [67] stands as a comprehensive and expansive dataset, capturing aerial images under diverse conditions and across varied terrains. Covering an array of object categories, including aircraft, AID serves as a comprehensive resource for both the training and testing of object detection models. The dataset's inclusion of object-level annotations assumes a pivotal role in facilitating the evaluation and refinement of aircraft detection algorithms. AID's inherent diversity ensures that models trained on this dataset demonstrate robust generalization capabilities across a spectrum of aerial imaging scenarios. This characteristic contributes significantly to the development of detection models characterized by heightened adaptability and precision. Notably, the AID dataset comprises 10,000 images including 360 aircrafts images distributed across 30 classes, providing a rich and varied dataset for advancing

Fig. 9. Sample Images from DOTA Dataset

research and applications in aerial image analysis [67, 73].

These images were extracted through Google Earth imagery, within dimensions of 600 × 600 pixels and a resolution ranging from 8 m to around 0.5 m [74].

H. Dataset for Object deTection in Aerial images (DOTA)

The DOTA dataset [16], tailored for large-scale object detection in aerial images, plays a pivotal role in the development and evaluation of object detectors under diverse real-world conditions. Capturing images from a variety of sensors and platforms, the dataset spans sizes from 800 × 800 to 20,000 × 20,000 pixels, showcasing objects with diverse scales, orientations, and shapes. Annotated by experts using arbitrary (8 dof.) quadrilaterals, DOTA has evolved through different versions. Focusing on aircraft detection, DOTA comprises 2806 aerial images from sources like Google Earth, with each image sized around 4000 × 4000 pixels. Annotating 15 objects using both orientated and horizontal bounding boxes, this study concentrates on identifying airplanes within the dataset, which includes 269 instances distributed between 198 training and 71 validation images. The spatial resolution, represented as Ground Sample Distance (GSD), varies from 0.09m to 4.2m, with an average of 0.40m and a standard deviation of 0.36m. DOTA's high-resolution images, coupled with meticulous annotations, position it as a valuable asset for training and rigorously assessing the efficacy of aircraft detection algorithms, particularly in challenging real-world scenarios [4, 10, 35, 36].

Fig. 9 [75] shows some samples of images for DOTA dataset.

I. Large-scale Extended Vehicle with aerial Image Remote sensing (LEVIR)

The LEVIR dataset [76] stands as a substantial resource in the realm of aerial image remote sensing. Comprising an extensive collection of Google Earth images, the dataset boasts more than 22,000 images, each sized at 600 × 800 pixels, and impressively labeled with over 10,000 individual targets [21].

Notably, the dataset is organized into three distinct categories of objects: aircraft, ships, and oil tanks, thereby providing a diverse set of targets for comprehensive analysis. The spatial resolution of the LEVIR dataset ranges from 0.2 to 1 meter [20], ensuring a varied and realistic representation of objects in high-resolution aerial imagery. Of particular interest is a subset within the dataset consisting of 4724 remote sensing (RS) images dedicated specifically to aircraft. Researchers and practitioners find the LEVIR dataset instrumental for advancing object detection algorithms, especially in the context of high-resolution aerial images captured from Google Earth.

J. Detection in Optical Remote sensing images (DIOR)

The DIOR dataset [69] stands as a comprehensive and openly accessible dataset designed for remote sensing image target detection, featuring 20 distinct target categories [77]. Comprising 23,463 optical Remote Sensing Images (RSIs) with a cumulative total of 192,472 instances, DIOR offers a diverse range of spatial resolutions spanning from 0.5 to 30 meters. The images encapsulate various environmental conditions, including variations in weather, season, and illumination, while maintaining consistent dimensions of 800 × 800 pixels [20].

Within the aircraft category, DIOR incorporates a total of 1,387 aircraft images [78]. This dataset serves as a valuable resource for advancing research in remote sensing image target detection, providing a rich variety of scenarios and targets to facilitate robust model training and evaluation.

K. Multi-Type Aircraft of Remote Sensing Images (MTARSI)

The MTARSI dataset [79], stands as a pioneering and publicly accessible resource, marking the first dataset to feature fine-grained aircraft classification for remote sensing images. Distinguished by its authoritative nature, the dataset has been meticulously labeled by seven experts in the field of remote sensing image interpretation, lending a high degree of credibility to its contents [80].

Comprising a total of 9,385 remote sensing images sourced from Google Earth satellite imagery, the dataset focuses on aircraft images, encompassing 36 different airports and featuring 20 distinct aircraft types [80, 81]. Noteworthy among the variety are aircraft models such as Boeing, F-22, C-5, A-10, B-1, C-130, B-2, C-17, B-29, C-135, B-52, E-3, F-16, KC-10, C-21, U-2, T-43, A-26, T-6, and P-63, offering a rich and diverse dataset for advancing research in fine-grained aircraft classification [79].

L. Synthetic Aperture Radar Data (SADD)

The SADD [82] is sourced from the German TerraSAR-X satellite, which operates in the x-band frequency and HH polarization mode, offering images with resolutions spanning from 0.5 to 3 meters. The dataset, composed of 7835 aircraft targets, along with structures, undergoes a cropping process to generate 2966 nonoverlapping slices, each measuring 224×224 pixels and featuring distinct outlines of critical components. Within the SADD dataset, the showcased aircraft targets exhibit a diverse range of sizes, with a notable proportion being relatively modest in scale [82, 83].

This dataset is a valuable resource for researchers and practitioners engaged in radar-based object detection, providing a curated collection of radar images capturing aircraft targets and their associated structures.

M. Military Aircraft Recognition Dataset

The Military Aircraft Recognition dataset stands as a significant contribution to the domain of remote sensing imagery, comprising 3,842 images of military aircraft. This dataset encompasses a diverse set of 20 distinct aircraft types, resulting in a total of 22,341 instances. Such a dataset serves as a valuable resource for advancing the field of military aircraft recognition, enabling researchers and practitioners to develop and assess algorithms tailored to the challenges of detecting and classifying military aircraft in remote sensing images. The inclusion of oriented bounding boxes adds a layer of sophistication, acknowledging the nuanced spatial orientation of these aircraft. Researchers seeking to enhance the robustness and precision of military aircraft recognition models can leverage this dataset for comprehensive training and evaluation [85].

Table IV summarizes the above-mentioned datasets.

VII. Evaluation Criteria

Evaluation metrics stand as a crucial method for assessing the effectiveness of aircraft detection algorithms, with Precision (P) , Recall (R), and F1-score being traditional metrics, and the Average Precision (AP) metric gaining prominence in recent years due to its derivation from precision and recall [57]. Before delving into specific metric formulations, it's essential to comprehend common concepts shared among them. The fundamental concepts include True Positive (TP) representing a correct detection of an existing aircraft, False Positive (FP) denoting an incorrect detection

of a nonexistent aircraft or an inaccurate detection of an actual object, True Negative (TN) indicating a correct detection of nonexistent aircraft, and False Negative (FN) signifying an incorrect detection of an existing aircraft.

Precision

Precision, denoted as the predicted region's percentage corresponding to the true region, is calculated using the following formula [77]:

$$P(\text{Precision}) = \frac{TP}{TP+FP} \tag{1}$$

Recall (or Sensitivity)

Recall, also known as Sensitivity, measures the proportion of the ground-truth region present in the anticipated region, expressed as [77, 84]:

$$R(\text{Recall}) = \frac{TP}{TP+FN} \tag{2}$$

F1-score

The F1-score, an average of recall and precision, is calculated as [77]

$$F1\text{-score} = \frac{2 \times P \times R}{P+R} \tag{3}$$

Average Precision (AP)

Average Precision (AP) [57], the most popular metric resulting from precision and recall, is evaluated in a category-specific manner, separately for each object category, and determined by the formula (4):

$$\text{AP} = \sum_{n} (R_n - R_(n-1))P_n \tag{4}$$

Where n is number of classes.

Mean Average Precision (mAP)

Mean Average Precision (mAP) [57], averaged across all object categories, serves as the final performance measure when comparing performance across categories and is calculated by (5).

$$\text{mAP} = \frac{1}{n}\sum_{i}^{n} AP_i \tag{5}$$

Accuracy

Accuracy (AC), a critical and standard measure, is defined as the ratio between correct samples to the number of total samples with the equation (6) [85].

$$\text{AC} = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

Specificity

Specificity is the proportion of accurately identified negative cases out of the total amount of instances that are truly negative.The specificity formula is given by:

$$\text{Specificity} = \frac{TP}{FP+TN} \tag{7}$$

TABLE IV.
POPULAR DATASETS FOR AIRCRAFT DETECTION

References	Dataset	Aircraft images	Image type	Image size (in pixels)	Started year
[63]	Caltech-101	800	Real-world images	300×200	2003
[65]	UC Merced Land	100	RSI	256×256	2010
[68]	UCAS-AOD	600	RSI	1000×1000	2015
[69]	NWPU VHR-10	664	RSI	958×808 and 1025×578	2016
[17]	RSOD	446	RSI	1072×975 and 1116×659	2017
[71]	NWPU-RESISC45	700	RSI	256×256	2017
[67]	AID	360	Aerial Images	600×600	2017
[16]	DOTA	269	RSI	4000×4000	2018
[69]	DIOR	1387	RSI	800×800	2018
[76]	LEVIR	4724	RSI	600×800	2018
[79]	MTARSI	9385	RSI	256×256	2020
[82]	SADD	7835	SAR images	640×480	2022

VIII. APPLICATIONS

An airplane is a versatile object that serves both civilian and military purposes, playing a crucial part in various aerial applications. Precise and swift detection of aircraft is a crucial element in both civilian and military domains Within the civilian sector, airplanes serve as a vital mode of transportation, and the ability to detect aircraft scan significantly aid in airport management [53]. In addition, the efficient identification of aircraft objects can enhance the efficiency of airports for civilian purposes, as well as guide aircraft parking upon landing [44].

In terms of military operations, the ability to identify aircrafts is quite essential. Gathering details about the types and quantities of aircrafts are beneficial for both air defense and carrying out military attacks [53]. Furthermore, efficient and precise collection data of aircraft targets in the airport and airspace is critical, as it can aid in the gathering of combat military intelligence and the formulation of battle plans in real-time [82].

A. Aircraft Inspection and Maintenance

Aircraft detection is employed in aviation for activities such as aircraft inspection and maintenance. Technicians employ deep learning to identify issues and discern damage patterns in aircraft using images, even those imperceptible to the unaided eye. Deep learning vision inspection enhances safety and mitigates the risk of accidents or operational disruptions. Furthermore, aircraft detection can be employed to inspect aircraft components automatically, hence diminishing the time and workforce needed for manual assessment. Additionally, it enhances the objectivity and uniformity of the judgement [86].

B. Airport Management

Aircraft detection plays a crucial role in airport operations, serving numerous purposes such as airport planning and environmental studies. Both research and commercial systems heavily rely on text recognition to identify aircraft tail numbers. This task is complex because of diminished visibility, visual obstructions, and the difficulty of reading tail numbers presented in different fonts, sizes, and orientations [87]. Therefore, it is necessary to implement a multi-step computer vision system based on deep learning in order to achieve more precise aircraft detection and identification.

C. Airport Security and Safety

Aircraft detection may also be utilized in security applications. By strategically placing cameras, airports can monitor the movements of aircrafts. Real-time updates of information and reports aid in the identification of potential security risks and enhance operational security [88].

IX. Challenges and Limitations

The field of aircraft detection using various technologies, particularly deep learning, presents several challenges and limitations that warrant careful consideration. One prominent challenge involves the availability and quality of annotated datasets, as the success of deep learning models heavily relies on extensive, well-annotated data for training [20]. The diversity of aircraft appearances [6], varying environmental conditions [21], and the need for real-world scenarios further complicate the dataset collection process. Additionally, the interpretability of deep learning models remains a challenge, raising concerns about the "black-box" nature of these algorithms and hindering their adoption in safety-critical applications [13].

Computational complexity and resource requirements constitute another limitation, as deploying sophisticated deep learning models for real-time, on-board applications may strain computational resources [27]. Moreover, addressing issues related to the generalization of models across diverse settings and adapting to dynamic environments poses ongoing research challenges. Ethical considerations, such as privacy concerns and potential misuse of detection technologies, add to the complexity of deploying these systems responsibly [89].

As the field progresses, addressing these challenges and limitations will be essential for advancing the reliability, efficiency, and ethical use of aircraft detection technologies in real-world applications.

X. Conclusion

Aircraft detection is one of the essential branches of object detection that has attracted the interest of numerous researchers, particularly since the advent of deep learning tools, which have significantly contributed to the field's advancement. This review paper demonstrates the general architecture of aircraft detection, sensor-based detection approaches, and image-based detection approaches. In addition, this review paper makes an exhaustive and detailed review of deep learning techniques for detecting aircraft comprising two-stage detectors, such as RCNN, Fast RCNN and Spatial Pyramid Pooling Networks (SPPNet) , and one-stage detectors, such as YOLO ,RetinaNet and SSD. As well as descriptions of commonly used aircraft detection datasets and evaluation metrics are provided. Researchers must consider several aspects of recent trends in deep learning-based aircraft detection, including the detection of small objects, aircraft detection in real-time, and detection in videos.

Conflict of Interest

The authors have declared no conflict of interest.

References

[1] J. Deng, X. Xuan, W. Wang, Z. Li, H. Yao, and Z. Wang, "A review of research on object detection based on deep learning," in *Journal of Physics: Conference Series*, vol. 1684, p. 012028, IOP Publishing, 2020. https://doi.org/10.1088/1742-6596/1684/1/012028.

[2] Y. Xiao, Z. Tian, J. Yu, Y. Zhang, S. Liu, S. Du, and X. Lan, "A review of object detection based on deep learning," *Multimedia Tools and Applications*, vol. 79, pp. 23729–23791, 2020. https://doi.org/10.1007/s11042-020-08976-6.

[3] N. Odey and A. Marhoon, "Feature deep learning extraction approach for object detection in self-driving cars," *Iraqi Journal for Electrical And Electronic Engineering*, vol. 19, no. 2, 2023. https://doi.org/10.37917/ijeee.19.2.8.

[4] M. Lu, Q. Li, L. Chen, and H. Li, "Scale-adaptive adversarial patch attack for remote sensing image aircraft detection," *Remote Sensing*, vol. 13, no. 20, p. 4078, 2021. https://doi.org/10.3390/rs13204078.

[5] M. Zhu, Y. Xu, S. Ma, S. Li, H. Ma, and Y. Han, "Effective airplane detection in remote sensing images based on multilayer feature fusion and improved nonmaximal suppression algorithm," *Remote Sensing*, vol. 11, no. 9, p. 1062, 2019. https://doi.org/10.3390/rs11091062.

[6] Y. Wang, H. Li, P. Jia, G. Zhang, T. Wang, and X. Hao, "Multi-scale densenets-based aircraft detection from remote sensing images," *Sensors*, vol. 19, no. 23, p. 5270, 2019. https://doi.org/10.3390/s19235270.

[7] R. Bhalara, R. J. Shilu, and D. Nandi, "A review on aircraft detection techniques and feature extraction using deep learning," *IJAEM*, vol. 7, pp. 305–307, 2020. https://doi.org/10.35629/5252-0205305307.

[8] K. Oksuz, B. C. Cam, S. Kalkan, and E. Akbas, "Imbalance problems in object detection: A review," *IEEE transactions on pattern analysis and machine intelligence*, vol. 43, no. 10, pp. 3388–3415, 2020. https://doi.org/10.1109/tpami.2020.2981890.

[9] S. S. A. Zaidi, M. S. Ansari, A. Aslam, N. Kanwal, M. Asghar, and B. Lee, "A survey of modern deep learning based object detection models," *Digital Signal Processing*, vol. 126, p. 103514, 2022. https://doi.org/10.1016/j.dsp.2022.103514.

[10] U. Alganci, M. Soydas, and E. Sertel, “Comparative research on deep learning approaches for airplane detection from very high-resolution satellite images,” *Remote sensing*, vol. 12, no. 3, p. 458, 2020. https://doi.org/10.3390/rs12030458.

[11] M. R. Mohammadi, “Deep multiple instance learning for airplane detection in high-resolution imagery,” *Machine Vision and Applications*, vol. 32, no. 1, p. 36, 2021. https://doi.org/10.1007/s00138-020-01153-7.

[12] H. Jia, Q. Guo, J. Chen, F. Wang, H. Wang, and F. Xu, “Adaptive component discrimination network for airplane detection in remote sensing images,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7699–7713, 2021. https://doi.org/10.1109/JSTARS.2021.3098296.

[13] R. Luo, J. Xing, L. Chen, Z. Pan, X. Cai, Z. Li, J. Wang, and A. Ford, “Glassboxing deep learning to enhance aircraft detection from sar imagery,” *Remote Sensing*, vol. 13, no. 18, p. 3650, 2021. https://doi.org/10.3390/rs13183650.

[14] Y. Zhao, J. Li, W. Li, P. Shan, X. Wang, L. Li, and Q. Fu, “Ms-iaf: Multi-scale information augmentation framework for aircraft detection,” *Remote Sensing*, vol. 14, no. 15, p. 3696, 2022. https://doi.org/10.3390/rs14153696.

[15] J. Kaur and W. Singh, “Tools, techniques, datasets and application areas for object detection in an image: a review,” *Multimedia Tools and Applications*, vol. 81, no. 27, pp. 38297–38351, 2022. https://doi.org/10.1007/s11042-022-13153-y.

[16] G.-S. Xia, X. Bai, J. Ding, Z. Zhu, S. Belongie, J. Luo, M. Datcu, M. Pelillo, and L. Zhang, “Dota: A large-scale dataset for object detection in aerial images,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 3974–3983, 2018. https://doi.org/10.1109/cvpr.2018.00418.

[17] Y. Long, Y. Gong, Z. Xiao, and Q. Liu, “Accurate object localization in remote sensing images based on convolutional neural networks,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 55, no. 5, pp. 2486–2498, 2017. https://doi.org/10.1109/tgrs.2016.2645610.

[18] J. A. Alhijaj and R. S. Khudeyer, “Integration of efficientnetb0 and machine learning for fingerprint classification,” *Informatica*, vol. 47, no. 5, 2023. https://doi.org/10.31449/inf.v47i5.4724.

[19] J. Wang, T. Zhang, Y. Cheng, and N. Al-Nabhan, “Deep learning for object detection: A survey.,” *Computer Systems Science & Engineering*, vol. 38, no. 2, 2021. https://doi.org/10.32604/csse.2021.017016.

[20] Z. Li, Y. Wang, N. Zhang, Y. Zhang, Z. Zhao, D. Xu, G. Ben, and Y. Gao, “Deep learning-based object detection techniques for remote sensing images: A survey,” *Remote Sensing*, vol. 14, no. 10, p. 2385, 2022. https://doi.org/10.3390/rs14102385.

[21] Z. Zou, K. Chen, Z. Shi, Y. Guo, and J. Ye, “Object detection in 20 years: A survey,” *Proceedings of the IEEE*, vol. 111, no. 3, pp. 257–276, 2023. https://doi.org/1905.05055.

[22] R. Kaur and S. Singh, “A comprehensive review of object detection with deep learning,” *Digital Signal Processing*, vol. 132, p. 103812, 2023. https://doi.org/10.1016/j.dsp.2022.103812.

[23] S. Gui, S. Song, R. Qin, and Y. Tang, “Remote sensing object detection in the deep learning era—a review,” *Remote Sensing*, vol. 16, no. 2, p. 327, 2024. https://doi.org/10.3390/rs16020327.

[24] L. Jiao, F. Zhang, F. Liu, S. Yang, L. Li, Z. Feng, and R. Qu, “A survey of deep learning-based object detection,” *IEEE access*, vol. 7, pp. 128837–128868, 2019. https://doi.org/10.1109/ACCESS.2019.2939201.

[25] Q. Liu, X. Xiang, Y. Wang, Z. Luo, and F. Fang, “Aircraft detection in remote sensing image based on corner clustering and deep learning,” *Engineering Applications of Artificial Intelligence*, vol. 87, p. 103333, 2020. https://doi.org/10.1016/j.engappai.2019.103333.

[26] M. A. Rafidison, H. M. Ramafiarisona, P. A. Randriamitantsoa, S. H. J. Rafanantenana, F. M. R. Toky, L. P. Rakotondrazaka, A. H. Rakotomihamina, *et al.*, “Image classification based on light convolutional neural network using pulse couple neural network,” *Computational Intelligence and Neuroscience*, vol. 2023, 2023. https://doi.org/10.1155/2023/7371907.

[27] R. Chandana and A. Ramachandra, “Real time object detection system with yolo and cnn models: A review,” *arXiv Prepr. arXiv2208*, vol. 773, 2022. https://doi.org/10.48550/arXiv.2208.00773.

[28] Y. Song and J. Tian, “Two-stage airplane detection with nms filtering in remote sensing images,” in *Proceedings of the 4th International Conference on Computer Science and Application Engineering*, pp. 1–5, 2020. https://doi.org/10.1145/3424978.3425114.

[29] H. L. Lee and D. H. Shim, "Multi-sensor fusion for enhanced aircraft detection in unmanned aerial systems integration," *IEEE Transactions on Aerospace and Electronic Systems*, 2021.

[30] R. George and J. Yang, "A survey for methods of detecting aircraft vortices," in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, vol. 45004, pp. 41–50, American Society of Mechanical Engineers, 2012. https://doi.org/10.1115/DETC2012-70632.

[31] M. H. Abd, G. A. Al-Suhail, F. R. Tahir, A. M. Ali Ali, H. A. Abbood, K. Dashtipour, S. S. Jamal, and J. Ahmad, "Synchronization of monostatic radar using a time-delayed chaos-based fm waveform," *Remote Sensing*, vol. 14, no. 9, p. 1984, 2022. https://doi.org/10.3390/rs14091984.

[32] G. Fasano, D. Accado, A. Moccia, and D. Moroney, "Sense and avoid for unmanned aircraft systems," *IEEE Aerospace and Electronic Systems Magazine*, vol. 31, no. 11, pp. 82–110, 2016. https://doi.org/10.1109/MAES.2016.160116.

[33] C. S. Pappu, A. N. Beal, and B. C. Flores, "Chaos based frequency modulation for joint monostatic and bistatic radar-communication systems," *Remote Sensing*, vol. 13, no. 20, p. 4113, 2021. https://doi.org/10.3390/rs13204113.

[34] M.-J. Lobo, C. Hurter, and M. Cousy, "A lidar interactive data visualization for ground aircraft detection at small airports," in *SID 2019, 9th SESAR Innovation Days*, 2019.

[35] J. Li, H. Zhao, X. Gu, L. Yang, B. Bai, G. Jia, and Z. Li, "Analysis of space-based observed infrared characteristics of aircraft in the air," *Remote sensing*, vol. 15, no. 2, p. 535, 2023. https://doi.org/10.3390/rs15020535.

[36] L. Zhang, Z. Zhai, L. He, P. Wen, and W. Niu, "Infrared-inertial navigation for commercial aircraft precision landing in low visibility and gps-denied environments," *Sensors*, vol. 19, no. 2, p. 408, 2019. https://doi.org/10.3390/s19020408.

[37] S. Agarwal, N. Panigarhi, and M. Rajesh, "Detection of aircraft in satellite images using multilayer convolution neural network," in *IFIP International Internet of Things Conference*, pp. 402–409, Springer, 2023.

[38] Rhammell, "Aircraft detection in satallite imagery." http://www.kaggle.com/datasets/rhammell/planesnet.

[39] K. Zhao and X. Ren, "Small aircraft detection in remote sensing images based on yolov3," in *IOP Conference Series: Materials Science and Engineering*, vol. 533, p. 012056, IOP Publishing, 2019. https://doi.org/10.1088/1757-899x/533/1/012056.

[40] H. Yan, "Aircraft detection in remote sensing images using centre-based proposal regions and invariant features," *Remote Sensing Letters*, vol. 11, no. 8, pp. 787–796, 2020. https://doi.org/10.1080/2150704X.2020.1770364.

[41] Z.-Z. Wu, T. Weise, Y. Wang, and Y. Wang, "Convolutional neural network based weakly supervised learning for aircraft detection from remote sensing image," *IEEE Access*, vol. 8, pp. 158097–158106, 2020. https://doi.org/10.1109/access.2020.3019956.

[42] Y. Wang, S. M. A. Bashir, M. Khan, Q. Ullah, R. Wang, Y. Song, Z. Guo, and Y. Niu, "Remote sensing image super-resolution and object detection: Benchmark and state of the art," *Expert Systems with Applications*, vol. 197, p. 116793, 2022. https://doi.org/10.1016/j.eswa.2022.116793.

[43] Q. Hu, R. Li, Y. Xu, C. Pan, C. Niu, and W. Liu, "Toward aircraft detection and fine-grained recognition from remote sensing images," *Journal of Applied Remote Sensing*, vol. 16, no. 2, pp. 024516–024516, 2022. https://doi.org/10.1117/1.jrs.16.024516.

[44] X. Chen, J. Liu, F. Xu, Z. Xie, Y. Zuo, and L. Cao, "A novel method of aircraft detection under complex background based on circular intensity filter and rotation invariant feature," *Sensors*, vol. 22, no. 1, p. 319, 2022. https://doi.org/10.3390/s22010319.

[45] P. Singh, M. Diwakar, A. Shankar, R. Shree, and M. Kumar, "A review on sar image and its despeckling," *Archives of Computational Methods in Engineering*, vol. 28, pp. 4633–4653, 2021. https://doi.org/10.1007/s11831-021-09548-z.

[46] P. Zhang, H. Xu, T. Tian, P. Gao, and J. Tian, "Sfre-net: Scattering feature relation enhancement network for aircraft detection in sar images," *Remote Sensing*, vol. 14, no. 9, p. 2076, 2022. https://doi.org/10.3390/rs14092076.

[47] J. Wang, H. Xiao, L. Chen, J. Xing, Z. Pan, R. Luo, and X. Cai, "Integrating weighted feature fusion and the spatial attention module with convolutional neural networks for automatic aircraft detection from sar images," *Remote Sensing*, vol. 13, no. 5, p. 910, 2021. https://doi.org/10.3390/rs13050910.

[48] Z. Sun, M. Dai, X. Leng, Y. Lei, B. Xiong, K. Ji, and G. Kuang, "An anchor-free detection method for ship targets in high-resolution sar images," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7799–7816, 2021. https://doi.org/10.1109/jstars.2021.3099483.

[49] S. Wei, X. Zeng, Q. Qu, M. Wang, H. Su, and J. Shi, "Hrsid: A high-resolution sar images dataset for ship detection and instance segmentation," *Ieee Access*, vol. 8, pp. 120234–120254, 2020. https://doi.org/10.1109/access.2020.3005861.

[50] R. Luo, L. Chen, J. Xing, Z. Yuan, S. Tan, X. Cai, and J. Wang, "A fast aircraft detection method for sar images based on efficient bidirectional path aggregated attention network," *Remote Sensing*, vol. 13, no. 15, p. 2940, 2021. https://doi.org/10.3390/rs13152940.

[51] J. Qin, H. Qu, H. Chen, and W. Chen, "Joint detection of airplane targets based on sar images and optical images," in *IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium*, pp. 1366–1369, IEEE, 2019. https://doi.org/10.1109/igarss.2019.8900167.

[52] M. Li, G. Wen, X. Huang, K. Li, and S. Lin, "A lightweight detection model for sar aircraft in a complex environment," *Remote Sensing*, vol. 13, no. 24, p. 5020, 2021. https://doi.org/10.3390/rs13245020.

[53] C. He, M. Tu, D. Xiong, F. Tu, and M. Liao, "A component-based multi-layer parallel network for airplane detection in sar imagery," *Remote Sensing*, vol. 10, no. 7, p. 1016, 2018. https://doi.org/10.3390/rs10071016.

[54] Y. Zhao, L. Zhao, Z. Liu, D. Hu, G. Kuang, and L. Liu, "Attentional feature refinement and alignment network for aircraft detection in sar imagery," *arXiv preprint arXiv:2201.07124*, 2022. https://doi.org/10.1109/tgrs.2021.3139994.

[55] M. Abdulla and A. Marhoon, "Agriculture based on internet of things and deep learning," *Iraqi Journal for Electrical and Electronic Engineering*, vol. 18, no. 2, pp. 1–8, 2022. https://doi.org/10.37917/ijeee.18.2.1.

[56] C. Cao, J. Wu, X. Zeng, Z. Feng, T. Wang, X. Yan, Z. Wu, Q. Wu, and Z. Huang, "Research on airplane and ship detection of aerial remote sensing images based on convolutional neural network," *Sensors*, vol. 20, no. 17, p. 4696, 2020. https://doi.org/10.3390/s20174696.

[57] L. Liu, W. Ouyang, X. Wang, P. Fieguth, J. Chen, X. Liu, and M. Pietikäinen, "Deep learning for generic object detection: A survey," *International journal of computer vision*, vol. 128, pp. 261–318, 2020. https://doi.org/10.1007/s11263-019-01247-4.

[58] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "Yolov4: Optimal speed and accuracy of object detection," *arXiv preprint arXiv:2004.10934*, 2020. https://doi.org/10.48550/arXiv.2004.10934.

[59] X. Zhang, D. Hu, S. Li, Y. Luo, J. Li, and C. Zhang, "Aircraft detection from low scnr sar imagery using coherent scattering enhancement and fused attention pyramid," *Remote Sensing*, vol. 15, no. 18, p. 4480, 2023. https://doi.org/10.3390/rs15184480.

[60] Z. A. Khalaf, A. Al-Mayyahi, A. Aldair, and P. Birch, "Airplane detection using deep learning based on vgg and svm," *Tikrit Journal of Engineering Sciences*, vol. 31, no. 3, pp. 202–211, 2024.

[61] J. Wang, Z. Bai, X. Zhang, and Y. Qiu, "A lightweight remote sensing aircraft object detection network based on improved yolov5n," *Remote Sensing*, vol. 16, no. 5, p. 857, 2024. https://doi.org/10.3390/rs16050857.

[62] J. Chen, Y. Shen, Y. Liang, Z. Wang, and Q. Zhang, "Yolo-sad: An efficient sar aircraft detection network," *Applied Sciences*, vol. 14, no. 7, p. 3025, 2024. https://doi.org/10.3390/app14073025.

[63] L. Fei-Fei, R. Fergus, and P. Perona, "Learning generative visual models from few training examples: An incremental bayesian approach tested on 101 object categories," in *2004 conference on computer vision and pattern recognition workshop*, pp. 178–178, IEEE, 2004. https://doi.org/10.1016/j.cviu.2005.09.012.

[64] A. S. Rao and K. Mahantesh, "Learning semantic features for classifying very large image datasets using convolution neural network. sn comput. sci. 2: 187," 2021. https://doi.org/10.1007/s42979-021-00589-6.

[65] Y. Yang and S. Newsam, "Bag-of-visual-words and spatial extensions for land-use classification," in *Proceedings of the 18th SIGSPATIAL international conference on advances in geographic information systems*, pp. 270–279, 2010. https://doi.org/10.1145/1869790.1869829.

[66] N. L. Tun, A. Gavrilov, N. M. Tun, H. Aung, *et al.*, "Remote sensing data classification using a hybrid pre-trained vgg16 cnn-svm classifier," in *2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus)*, pp. 2171–2175, IEEE, 2021. https://doi.org/10.1109/ElConRus51938.2021.9396706.

[67] G.-S. Xia, J. Hu, F. Hu, B. Shi, X. Bai, Y. Zhong, L. Zhang, and X. Lu, "Aid: A benchmark data set for performance evaluation of aerial scene classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 55, no. 7, pp. 3965–3981, 2017. https://doi.org/10.1109/TGRS.2017.2685945.

[68] H. Zhu, X. Chen, W. Dai, K. Fu, Q. Ye, and J. Jiao, "Orientation robust object detection in aerial images using deep convolutional neural network," in *2015 IEEE International Conference on Image Processing (ICIP)*, pp. 3735–3739, IEEE, 2015. https://doi.org/10.1109/icip.2015.7351502.

[69] Z. Yan, X. Song, H. Zhong, and X. Zhu, "Object detection in optical remote sensing images based on transfer learning convolutional neural networks," in *2018 5th IEEE International Conference on Cloud Computing and Intelligence Systems (CCIS)*, pp. 935–942, IEEE, 2018. https://doi.org/10.1109/CCIS.2018.8691238.

[70] Y. Yang, G. Xie, and Y. Qu, "Real-time detection of aircraft objects in remote sensing images based on improved yolov4," in *2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, pp. 1156–1164, IEEE, 2021. https://doi.org/10.1109/iaeac50856.2021.9390673.

[71] G. Cheng, J. Han, and X. Lu, "Remote sensing image scene classification: Benchmark and state of the art," *Proceedings of the IEEE*, vol. 105, no. 10, pp. 1865–1883, 2017. https://doi.org/10.1109/JPROC.2017.2675998.

[72] J. Yang, G. Cheng, X. Yao, J. Han, and L. Guo, "Learning region response ranking features for remote sensing image scene classification," in *IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium*, pp. 529–532, IEEE, 2019. https://doi.org/10.1109/igarss.2019.8897886.

[73] P. Jin, G.-S. Xia, F. Hu, Q. Lu, and L. Zhang, "Aid++: An updated version of aid on scene classification," in *IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium*, pp. 4721–4724, IEEE, 2018. https://doi.org/10.1109/IGARSS.2018.8518882.

[74] S. Li, J. Guo, J. Li, W. He, and K. Zhao, "Triple attention vision transformers for remote sensing image classification," in *2023 IEEE 6th International Conference on Electronic Information and Communication Technology (ICEICT)*, pp. 568–573, IEEE, 2023. https://doi.org/10.1109/iceict57916.2023.10245719.

[75] Q. Wu, D. Feng, C. Cao, X. Zeng, Z. Feng, J. Wu, and Z. Huang, "Improved mask r-cnn for aircraft detection in remote sensing images," *Sensors*, vol. 21, no. 8, p. 2618, 2021. https://doi.org/10.3390/s21082618.

[76] Z. Zou and Z. Shi, "Random access memories: A new paradigm for target detection in high resolution aerial remote sensing images," *IEEE Transactions on Image Processing*, vol. 27, no. 3, pp. 1100–1111, 2017. https://doi.org/10.1109/tip.2017.2773199.

[77] M. Ahmed, K. A. Hashmi, A. Pagani, M. Liwicki, D. Stricker, and M. Z. Afzal, "Survey and performance analysis of deep learning based object detection in challenging environments," *Sensors*, vol. 21, no. 15, p. 5116, 2021. https://doi.org/10.3390/s21155116.

[78] L. Shi, Z. Tang, T. Wang, X. Xu, J. Liu, and J. Zhang, "Aircraft detection in remote sensing images based on deconvolution and position attention," *International Journal of Remote Sensing*, vol. 42, no. 11, pp. 4241–4260, 2021. https://doi.org/10.1080/01431161.2021.1892858.

[79] Z.-Z. Wu, S.-H. Wan, X.-F. Wang, M. Tan, L. Zou, X.-L. Li, and Y. Chen, "A benchmark data set for aircraft type recognition from remote sensing images," *Applied Soft Computing*, vol. 89, p. 106132, 2020. https://doi.org/10.1016/j.asoc.2020.106132.

[80] W. Tang, C. Deng, Y. Han, Y. Huang, and B. Zhao, "Srarnet: A unified framework for joint super-resolution and aircraft recognition," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 327–336, 2020. https://doi.org/10.1109/JSTARS.2020.3037225.

[81] B. Zhao, W. Tang, Y. Pan, Y. Han, and W. Wang, "Aircraft type recognition in remote sensing images: Bilinear discriminative extreme learning machine framework," *Electronics*, vol. 10, no. 17, p. 2046, 2021. https://doi.org/10.3390/electronics10172046.

[82] P. Zhang, H. Xu, T. Tian, P. Gao, L. Li, T. Zhao, N. Zhang, and J. Tian, "Sefepnet: Scale expansion and feature enhancement pyramid network for sar aircraft detection with small sample dataset," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 3365–3375, 2022. https://doi.org/10.1109/JSTARS.2022.3169339.

[83] M. Huang, W. Yan, W. Dai, and J. Wang, "Est-yolov5s: Sar image aircraft target detection model based on improved yolov5s," *IEEE Access*, 2023. https://doi.org/10.1109/access.2023.3323575.

[84] Z. A. Khalaf, S. S. Hammadi, A. K. Mousa, H. M. Ali, H. R. Alnajar, and R. H. Mohsin, "Coronavirus disease 2019 detection using deep features learning.," *International Journal of Electrical & Computer Engineering (2088-8708)*, vol. 12, no. 4, 2022. https://doi.org/10.21203/rs.3.rs-60331/v1.

[85] G. S. Ohannesian and E. J. Harfash, "Epileptic seizures detection from eeg recordings based on a hybrid system of gaussian mixture model and random forest classifier," *Informatica*, vol. 46, no. 6, 2022. https://doi.org/10.31449/inf.v46i6.4203.

[86] Z.-H. Chen and J.-C. Juang, "Yolov4 object detection model for nondestructive radiographic testing in aviation maintenance tasks," *AIAA journal*, vol. 60, no. 1, pp. 526–531, 2022. https://doi.org/10.2514/1.j060860.

[87] A. Chatterjee, H. Flores, S. Sen, K. S. Hasan, and A. Mani, "Distributed location detection algorithms using iot for commercial aviation," in *2017 Third International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN)*, pp. 126–131, IEEE, 2017. https://doi.org/10.1109/icrcicn.2017.8234493.

[88] E. Habler, R. Bitton, and A. Shabtai, "Assessing aircraft security: A comprehensive survey and methodology for evaluation," *ACM Computing Surveys*, vol. 56, no. 4, pp. 1–40, 2023. https://doi.org/10.1145/3610772.

[89] V. Chang, Z. Ji, and M. Arami, "Privacy and ethical issues of big data in the airline industry," in *4th International Conference on Complexity, Future Information Systems and Risk*, pp. 139–148, SciTePress, 2019. https://orcid.org/0000-0002-8012-5852.