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Research Article

A Survey on Real-Time Object Detection for UAV-Based Applications

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Abstract

An extensive review of real-time object identification methods for UAV-based applications is provided in this work. The study focuses on multimodal frameworks, lightweight detection techniques, small-object detection methods, and deep learning-based approaches, especially YOLO-based models. The annotated publications access methodology for the stated period is reminiscent of studies published from 2019 to 2025. The publications were sourced through the use of relevant keywords associated with UAV object detection and real-time systems within the vast scientific databases of IEEE Xplore, ScienceDirect, and SpringerLink.

The selected research papers were analyzed and classified into four main categories: multimodal detection systems, lightweight and edge computing models, attention mechanisms for small object detection, and YOLO-based detectors. Research papers were compared and evaluated based on detection accuracy, computational efficiency, and real-time operational viability on resource-constrained UAV platforms. The results indicated that YOLO-based models, while achieving rapid inference times, were still unable to detect small and spatially clustered objects sufficiently. On the other hand, advanced designs tended to significantly increase the computational burden leading to negative impact on the real-time aspect of the system, even though the designs improved detection accuracy.

The assessment identifies and highlights potential research directions, including practical design solutions for lightweight models and the challenges posed by small object size, limited computational resources, and the need for real-time performance.

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1.1 Introduction

Unmanned aerial vehicles, or UAVs, have been used by a variety of industries to provide instantaneous analysis and data collection. These industries include precision farming, aerial photography, disaster relief, aerial surveys and reconnaissance, and more [1][2][3]. UAVs are now being used more often for environmental monitoring, assessing burned forests, and tracking migratory marine and bird species, in addition to their use in security and military applications. This is due to recent developments in navigation systems, onboard sensors, multispectral cameras, and guidance technologies [1][4]. One crucial feature of UAV systems that run entirely on their own is the capacity to accurately identify and track objects. Numerous factors related to aerial photography make this work challenging, including varying elevations and perspectives above ground, limited picture quality, blur from the UAV's speed, background clutter, and the object's tiny size in relation to the visible area. Additionally, the processing capabilities of onboard UAV platforms are usually quite restricted, which significantly restricts both the speed of inference and the complexity of models[2][5][6]. Many studies have looked at techniques to recognize one or more item kinds, such as "vehicles" and "pedestrians," but many sophisticated uses of UAV technology depend on the ability to detect and identify many things in real-time.[2][6]. The development of precise and effective methods for recognizing and finding a range of items in a UAV's surroundings has previously been the subject of much study. The most notable advancements in object recognition capabilities have come from the development of deep learning and convolutional neural networks (CNNs) for computer vision, which enable the model to learn features automatically rather than depending on pre-formed (handcrafted) characteristics [3][7]. When it comes to real-time detectors, one-stage deep learning techniques have been a prominent line of inquiry. One such strategy that has drawn a lot of interest for this reason is the YOLO (You Only Look Once) family of models. These models enable quick, end-to-end inference for time-sensitive tasks carried out by UAVs (Unmanned Aerial Vehicles) by reformulating object detection into a single regression issue[7][8]. The YOLOv8 model, the most recent iteration of the YOLO series, incorporates technological advancements including PANet and CSP to improve speed and accuracy for usage in dynamic contexts, like those connected to drones (UAVs) [9][10]. In a variety of applications, including smart agriculture, urban security, traffic management optimization, post-disaster evaluation, and search and rescue operations, the YOLOv8 algorithm yields exceptional results [9]. YOLO has outperformed rival algorithms like DPM and Faster R-CNN in several detection settings[8][10][11]. Based on previous discussions, this paper describes the latest developments in object detection and tracking with UAVs. It compares the performance of YOLOv8 with other algorithms like YOLOv5 or Faster R-CNN and examines how well it can detect and track objects at multiple resolutions using aerial imagery. Other factors include the difficulties UAVs now have in detecting and tracking things in real time, as well as the necessity to improve UAVs' capacity to achieve this objective in the future. Despite a great deal of study, there are still basic problems with UAV-based object detection systems that need to be fixed, such as their inability to identify tiny things accurately, operate in real time, and evaluate data rapidly. Some of the most current studies on overcoming these challenges are highlighted in the next section.

Even while UAV-based object detection has made great strides, there are still a number of issues that need to be addressed. Current research frequently finds it difficult to sustain real-time performance while recognizing tiny and widely dispersed objects in complex aerial scenes. Furthermore, a lot of methods are tested in controlled environments and fail to take into account real-world limitations such limited onboard processing power and fluctuating ambient conditions.

Furthermore, existing survey studies either lack an organized comparison of approaches created especially for UAV-based real-time applications or concentrate on broad object detection algorithms. The trade-offs between detecting precision, processing economy, and real-time practicality become unclear as a result.

In order to overcome these constraints, this survey offers an organized and thorough analysis of current UAV-based object detection methods, with an emphasis on real-time performance. This work's primary contributions are as follows: (1) classifying current approaches into four major groups; (2) offering a comparative analysis based on computational efficiency and performance; and (3) highlighting important issues and potential future research areas for enhancing UAV-based object detection systems.

1.2 Overview of UAV Systems

Drones, sometimes referred to as unmanned aerial vehicles (UAVs), are autonomous or remotely piloted aerial platforms that include embedded processing units, sensors, and communication systems on board. The capacity of UAVs to carry out a variety of duties, including surveillance, environmental monitoring, infrastructure inspection, and disaster management, has drawn a lot of interest in recent years[12][13]. They are vital instruments for both military and civilian purposes because of their capacity to record aerial data in real time.

The flight control system, onboard sensors, propulsion system, communication module, and ground control station (GCS) are some of the essential parts of a typical UAV system [12]. While onboard sensors like cameras, the Global Positioning System (GPS), and inertial measurement units (IMU) supply the positional and environmental data needed for autonomous operation, the flight controller is in charge of stabilizing the UAV and overseeing navigation duties. The motors and propellers that make flying and maneuverability possible are part of the propulsion system[14].

UAV operations depend on constant communication between the UAV and external control systems, such the Ground Control Station or cloud-based traffic management systems, as per the system architecture outlined in recent research[13]. For UAV operations to be safe and dependable, real-time monitoring, control, and data transfer are made possible via this connectivity.

Fixed-wing, rotary-wing, and hybrid UAVs are among the several types of UAV platforms that may be categorized according to their construction and operating characteristics[12]. Because they can hover and maneuver, rotary-wing UAVs, like quadcopters, are frequently utilized for surveillance and inspection activities.

However, because of their greater speed and energy efficiency, fixed-wing UAVs are better suited for long-range missions.

The components and design of UAV systems are crucial in determining system performance from the standpoint of real-time object detection. The quality of recorded data is directly impacted by onboard sensors like cameras, which has an impact on detection accuracy, particularly for tiny objects. Furthermore, the complexity of detection models that may be used in real-time applications is severely constrained by the restricted computing power of onboard processing units.

Additionally, the kind of UAV platform—rotary-wing or fixed-wing—affects motion dynamics, flight altitude, and image stability, all of which have an impact on how well object detection algorithms work. Therefore, creating effective and dependable real-time object detection techniques requires a grasp of UAV system features.

1.3 UAV Algorithms and Communication Systems

For autonomous navigation, steady flying, and effective communication, UAV systems depend on a variety of algorithms. These algorithms fall into four general categories: perception algorithms, communication protocols, navigation algorithms, and flight control algorithms.

Accurate trajectory tracking and UAV stability are maintained using flight control algorithms [15]. Common control systems include proportional-integral-derivative (PID) controllers, adaptive control, and model predictive control. These algorithms continuously process sensor data to adjust motor speeds and maintain stable flying conditions. Autonomous UAV platforms often contain intelligent control systems that enable autonomous mission execution and decision-making[15].

Navigation algorithms enable UAVs to determine their position and choose the optimal flight paths. These algorithms often make use of GPS, IMU sensors, and path planning methods like A* and simultaneous localization and mapping (SLAM). These tactics allow UAVs to navigate difficult terrain and steer clear of obstacles.

Communication is crucial to UAV operations because it enables data exchange between the UAV, ground control station, and external devices [13]. Wireless communication technologies including Wi-Fi, radio frequency (RF), cellular networks (4G/5G), and satellite communication are commonly used in UAV communication systems. Video feeds, control commands, and telemetry data may all be transmitted in real time across these communication channels[13].

Specialized communication protocols like MAVLink and MQTT are also essential to modern UAV systems in order to guarantee dependable and effective data transfer between UAV components and control systems. These protocols provide remote control, real-time monitoring, and interaction with cloud platforms and traffic management systems[13].

In order to facilitate intelligent perception and object recognition, UAV systems are also progressively incorporating deep learning algorithms and artificial intelligence. These algorithms increase the autonomy and operational efficiency of UAVs by enabling real-time object detection, classification, and tracking.

UAV algorithms and communication methods have a significant impact on system responsiveness and detection performance in real-time object detection. The precision of detection is directly impacted by the stability of recorded video, which is influenced by navigation and flight control algorithms. In a similar vein, real-time data transfer between the UAV and ground control stations or edge-cloud systems is made possible via communication technologies.

In situations when detection responsibilities are largely delegated to external processing units, effective communication protocols are especially crucial. However, latency and communication issues might cause delays that impact the performance of real-time detection. For UAV-based applications to achieve precise and real-time object detection, effective algorithms and dependable communication systems must be integrated.

1.4 Survey Methodology

A comprehensive assessment of current studies on real-time object detection for UAV-based applications was used to carry out this survey. Major scientific databases such as IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar were consulted in order to gather pertinent studies. To guarantee coverage of the most current advancements in the discipline, the selection process concentrated on peer-reviewed journal articles and conference papers released between 2019 and 2025.

Studies addressing UAV-based object detection, real-time detection performance, lightweight and edge-aware detection models, and multimodal detection strategies were taken into consideration by the inclusion criteria. The survey did not include papers that addressed UAV-specific restrictions or those only addressed ground-based object detection.

A number of important criteria, including as detection architecture, computing efficiency, deployment viability on resource-constrained UAV platforms, and detection accuracy, were used to evaluate each chosen work. The examined techniques were then methodically divided into four primary groups: multimodal detection frameworks, attention-enhanced tiny object detection techniques, lightweight and edge-aware detection models, and YOLO-based real-time detection techniques.

In addition to highlighting important research trends, obstacles, and future research objectives, this structured methodology guarantees a thorough and impartial examination of existing UAV-based object detection systems.

Despite the survey's methodical approach, a number of limitations should be noted. Only papers from 2019 to 2025 that were indexed in major scientific databases were included in the selection of research, which may have excluded pertinent earlier works. Additionally, bias may be introduced when comparing performance outcomes due to variations in datasets, assessment measures, and experimental settings among the examined research.

Additionally, rather of using uniform experimental validation, the study is dependent on published data from the literature, which might compromise the consistency of comparisons. When analyzing the results of this survey, certain considerations should be taken into account.

1.5 Contributions of this Survey

The following is a summary of this survey's primary contributions: • Offering a thorough and current analysis of real-time object detection techniques for applications involving unmanned aerial vehicles. • Outlining a methodical taxonomy that divides current UAV object recognition techniques into four main categories: multimodal detection frameworks, lightweight and edge-aware models, attention-enhanced tiny object detection techniques, and YOLO-based techniques. • Comparing current detection models according to their computational effectiveness, detection accuracy, and applicability for use on UAV platforms with limited resources. • Determining the main obstacles to UAV-based real-time object detection, such as tiny object sizes, computational limits, and real-time processing limitations. • Outlining potential avenues for future study to enhance the detection capabilities, computational effectiveness, and practical implementation of UAV-based object detection systems.

2. Related Work

By modifying detection models intended for the ground view and retraining them using the UAV general dataset to provide fresh training data based on what the UAV can observe, UAV-based real-time item identification was initially studied. The use of YOLOv3 to identify objects in the aerial domain was among the earliest instances of this. YOLOv3 outperformed YOLOv3 without retraining when it was retrained to recognize items in the aerial domain. It was able to detect things with a comparatively high level of accuracy regardless of the aerial image's backdrop and flight altitude. Additionally, YOLOv3 demonstrated real-time capability in recognizing cars and people, averaging about 15 frames per second[5]. The accuracy of small and closely spaced object detection from complex aerial imagery was limited by older YOLO designs (mostly from the first half of this decade) that did not make use of multi-scale feature fusion and attention mechanisms, both of which had been developed in the last few years, despite being effective at the point of detection.

Through the use of increasingly sophisticated architectural designs, YOLO has improved in both detection accuracy and inference speed in later stages of development. When applied to drone video footage, YOLOv8 outperforms both YOLOv5 and Faster R-CNN in terms of performance. This was especially evident across a variety of flight heights and video quality formats[9]. Despite these benefits and their widespread usage as baseline systems, YOLOv8-based systems were seldom ever changed to address tiny object detection, congested sceneries, or power-efficient deployment to embedded UAV systems.

In order to optimize the capabilities of onboard computer hardware, researchers are creating a cooperative method for processing data from Unmanned Aerial Vehicles (UAVs) by utilizing edge-cloud frameworks. The Edge-YOLO system maintains the real-time frame rates necessary for extensive UAV surveillance scenarios while increasing detection accuracy through onboard and cloud-based processing.[16]. Nevertheless, these systems are susceptible to issues like network communication delays (latency) and connectivity disruptions. Additionally, they don't expressly aim to increase the accuracy of tiny item recognition in areas with a high density of flying objects.

Simultaneously, lightweight models were created to enable tiny, low-power UAV platforms and for real-time application. For the identification of tiny objects in aerial photography, LEAF-YOLO offers a new, lightweight, optimized version of the YOLO architecture with lower model complexity and competitive performance.[17]. Although this approach improves computing efficiency, it has not been validated for usage in long-range actual UAV operations, and reducing model capacity may potentially impair detection capabilities in highly complex and partially obscured environments.

New study has enhanced multi-scale feature representation for tiny object recognition. When a multilayer feature reconstruction technique was added to YOLOv10, it improved the ability to recognize extremely small and closely spaced objects from UAV (unmanned aerial vehicle) photographs without appreciably increasing the amount of computing needed to carry out this task[18].

However, compared to the smaller forms of the YOLOv10 model, the enhanced performance leads to an increase in the computational complexity of the model. There is currently no research on this model's increased power consumption or suitability for deployment on low power UAV platforms.

In order to improve feature discrimination in the intricate aerial image (scene), attention has been used. For instance, it has been demonstrated that combining edge enhancement filtering with attention mechanisms significantly improves the recognition of tiny objects from UAV photos, particularly in regions with crowded backgrounds[19]. Many of these approaches currently lack the proper hardware or software implementation on embedded systems, despite the fact that much progress has been made in obtaining reliable findings using a variety of ways.

To improve the resilience of object detection in less-than-ideal illumination, researchers have also employed thermal infrared cameras in addition to investigating the usage of RGB picture capture techniques. Using UPDT-based (UAV-Object Detection Technology) objects and multi-frame processing approaches, the authors proposed an embedded (UAV) system that employs the YOLOv8s algorithm to identify numerous objects in real-time (at night) with huge Object Detection heads for tiny targets.[20]. However, generalization across various environmental circumstances may be limited if heat data alone is used without including RGB information, particularly during daytime operations.

In order to improve resilience against occlusion and size fluctuation, some research integrated temporal tracking into object detection systems. Tracking accuracy and detection stability were enhanced across video sequences by combining tracking modules with UAV-trained detection algorithms [3]. Similarly, on UAV platforms, combining a Siamese-based tracking network with a pruned YOLOv4 detector preserved real-time performance while lowering computing complexity [6]. However, these methods frequently depended on outdated detection architectures, only addressed a restricted number of object categories, and failed to sufficiently improve tracking and detection for situations involving tiny objects.

The overall efficacy of deep learning techniques for aerial surveillance tasks was demonstrated by more extensive studies into deep learning-based object recognition and tracking for UAV images, which assessed many end-to-end models in a range of environmental circumstances[21]. These research, however, usually lacked thorough comparisons with contemporary YOLO-based and edge-oriented systems, rigorous real-time limitations, and specific architectural modifications for tiny object detection.

Based on the reviewed studies, existing UAV-based object detection approaches

can be broadly categorized into four main directions:
(1) YOLO-based real-time detectors, (2) lightweight and edge-aware models, (3) attention-enhanced and small-object-focused methods, and (4) multimodal and thermal-based detection frameworks. This categorization highlights the research trends and reveals key gaps that motivate further investigation.

Table 1: Evaluation of Current UAV-Based Real-Time Object Detection Techniques in Comparison.

No.	Study	Year	Dataset	Model / Method	Task	Key Results
1	Real-Time Object Detection Based on UAV	2019	UAV123, CARPK, Campus	YOLOv3 (Retrained)	Detection	~15 FPS, improved accuracy over original YOLOv3
2	Real-Time Object Detection Using YOLO-8: A Drone-Based Approach	2025	Drone videos (various altitudes)	YOLOv8	Detection	Accuracy ≈ 91%, faster than YOLOv5 & Faster R-CNN
3	Edge-YOLO: Real-Time Intelligent Object Detection	2022	UAV images & videos	Edge-YOLO (Edge–Cloud)	Detection	High mAP with real-time performance on edge devices
4	LEAF-YOLO: Lightweight Edge-Real-Time Small Object Detection	2024	Aerial imagery (UAV)	LEAF-YOLO	Detection (Small objects)	Improved small-object mAP with reduced parameters
5	MFR-YOLOv10: Object Detection in UAV-Taken Images	2025	VisDrone, InfraredData	YOLOv10 + MFR + Attention	Detection	mAP ↑ vs YOLOv10s, lightweight & real-time
6	Intelligent Detection Method of Small Targets in UAV	2025	VisDrone2019	Attention + Edge Enhancement	Detection (Small targets)	mAP@0.5 ≈ 43.3, competitive with YOLOv8
7	Reliable UAV-Based Thermal Infrared Target Detection	2025	Thermal UAV Dataset	YOLOv8s + MFP	Detection (Thermal / Night)	mAP@0.5 ≈ 96.4, 83 FPS
8	Object Detection and Tracking with UAV Data Using DL	2020	UAV123	DSOD + LSTM	Detection + Tracking	Precision 96.13%, Recall 95.28%
9	Real-Time Object Detection and Tracking for UAVs	2023	COCO + UAV videos	Pruned YOLOv4 + SiamMask	Detection + Tracking	mAP@0.5 ≈ 0.736, Params ↓ to 4.28M
10	Deep Learning for UAV-Based Object Detection and Tracking	2021	UAV datasets	CNN-based DL models	Detection + Tracking	Improved detection accuracy under UAV conditions

A number of significant findings on the effectiveness of UAV-based real-time object detection techniques are shown by the comparison shown in Table 1. YOLO-based models, especially YOLOv8, show excellent real-time performance and high detection accuracy across a variety of flying situations and datasets. However, when handling small and widely dispersed objects, particularly in intricate aerial sceneries like the VisDrone dataset, their performance tends to deteriorate.

Lightweight models, like LEAF-YOLO, are appropriate for deployment on resource-constrained UAV platforms because to their increased computing efficiency and decreased model complexity. However, in difficult settings with occlusion or high item density, this reduction in model size might result in a drop in detection accuracy.

However, sophisticated models like MFR-YOLOv10 that use attention processes and multi-scale feature reconstruction greatly enhance tiny object detection performance. These advancements, however, come at the According to the comparison research, the majority of lightweight YOLO-based models work in real-time on UAV platforms; nevertheless, their detection accuracy is still restricted in scenarios involving dense tiny objects, especially on difficult datasets like VisDrone. On the other hand, more intricate designs increase accuracy at the cost of increased processing, which limits their use in embedded UAV systems.

3. Taxonomy of UAV-Based Real-Time Object Detection Methods

UAV-based real-time object detection techniques may be methodically divided into four major classes based on the examined literature.

expense of greater processing complexity, which would restrict their use in real-time UAV systems.

Additionally, multimodal techniques, especially those that include RGB and thermal data, provide encouraging outcomes in enhancing detection robustness in low light and at night. These techniques may have problems with generalization when used in various environmental settings, despite their excellent accuracy.

Overall, the research shows a distinct trade-off between real-time speed and detection accuracy. In UAV-based object detecting systems, striking the ideal balance between these variables continues to be a major issue.

These include multimodal and thermal-based detection frameworks, attention-driven tiny object detection algorithms, lightweight and edge-aware models, and YOLO-based approaches. This taxonomy identifies important research avenues in the subject and offers an organized summary of current methodologies.

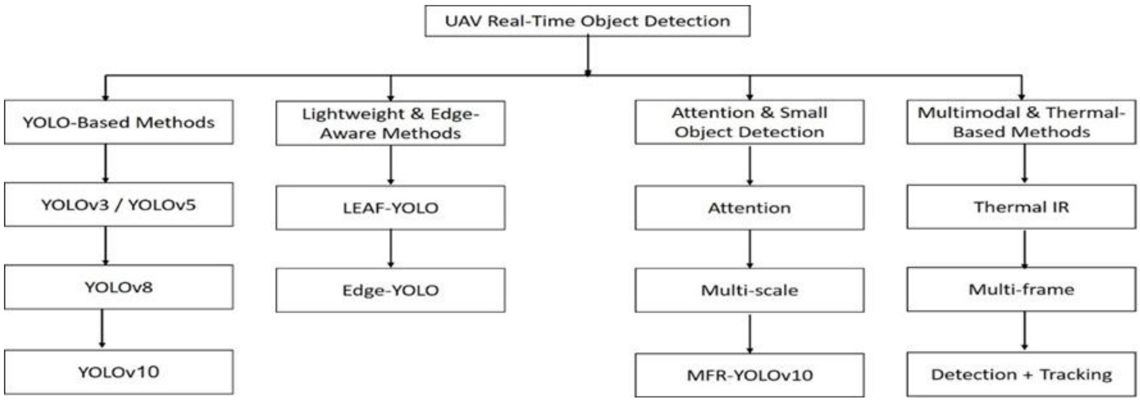

Figure 1: Taxonomy of real-time object detection methods for UAV-based applications.

4. Challenges

It's still difficult to identify and follow items in drone footage. The most obvious of these issues are the visual noise of uneven lighting, the flying speed, and the uncrewed aerial vehicle's (UAV) continuous vibrations, which all degrade video quality. The majority of vision algorithms rely on small details, which might be lost as a result of these problems. The issue of the scene's pictures occasionally having different intensities makes this worse. Changes in illumination angle, shadows, reflections, and the item itself may all affect an object's brightness. This can lead the model to see the object in different ways and make it more difficult to extract features for reliable and consistent identification.

The tiny size of the items in the aerial photos is another issue. Because of the aircraft's height, items in the picture look extremely small—in certain situations, they may be as little as a few pixels. As a result, the model has less access to visual information. This makes it harder for the model to recognize them precisely. When real-time detection and monitoring are needed, this issue gets worse. The required precision is directly impacted by the drone's onboard processors, which frequently have limited capacity and place strict limits on processing speed. Additionally, the models utilized must be lightweight and efficient.

5. Discussion

The literature study indicates that in UAV-based systems, there is a definite trade-off between real-time performance and detection accuracy. Even more modern YOLO-based models are capable of high inference rates, their ability to detect tiny and widely dispersed objects is still restricted in real-world UAV scenarios.

Furthermore, a lot of current methods are tested in controlled or dataset-specific settings, which could not accurately reflect real-world deployment settings. In experimental evaluations, variables like fluctuating flight altitude, weather, and hardware constraints are frequently disregarded.

These findings suggest that hardware-aware optimization, UAV-specific model creation, and thorough testing across a range of datasets and deployment scenarios should be given top priority in future UAV detection systems.

6. Future Research Directions

Even though UAV-based real-time object detection has advanced recently, there are still a number of unresolved issues that need to be investigated further. Enhancing tiny item recognition in complicated aerial landscapes and with extreme scale fluctuation remains a top priority, especially when time is of the essence. To tackle these problems, lightweight attention techniques and more efficient multi-scale feature representation are required.

Creating hardware-aware and energy-efficient detection models that can be deployed on UAV platforms with limited resources is another crucial avenue. Methods like neural architecture search, quantization, and model pruning are viable ways to strike a compromise between inference speed and detection accuracy.

Additionally, chances to improve resilience under difficult environmental circumstances are presented by multimodal data fusion, such as the integration of RGB and thermal images. Lastly, to better represent real-world deployment settings, future research should prioritize uniform assessment methodologies and UAV-specific standards.

7. Limitations of this Survey

This survey has a number of drawbacks even though it offers a thorough analysis of current real-time object detection techniques for UAV-based applications. First, because deep learning-based detection techniques are so widely used in UAV applications, the study mostly concentrates on YOLO-based and related architectures. Second, in order to highlight current developments in the area, the study primarily takes into account research that were published between 2019 and 2025. Some previous fundamental research might not have received as much attention as they should have because of this.

Furthermore, this survey's evaluation is predicated on the performance of detection models as stated in the reviewed literature; direct comparisons across approaches may be impacted by variations in datasets, hardware platforms, and experimental settings.

Future studies could broaden their focus to cover other UAV-related activities including multi-UAV coordination, autonomous navigation, and real-world deployment difficulties.

8. Conclusion

With an emphasis on YOLO-based approaches, lightweight and edge-aware models, attention-driven tiny object detection strategies, and multimodal detection frameworks, this survey examined current developments in real-time object detection for UAV-based applications. The investigation shows that although real-time performance has improved significantly, problems with small object detection, computational limitations, and practical implementation still exist.

Overall, the reviewed works show that on resource-constrained UAV platforms, there is a noticeable trade-off between detection accuracy and inference efficiency. UAV-specific model creation, hardware-aware optimization, and more thorough testing under actual operating circumstances are necessary to overcome these constraints. Future studies that incorporate multimodal sensing, effective attention mechanisms, and defined standards are anticipated to enhance the dependability and relevance of UAV-based object detection systems.

This survey highlights the significance of creating balanced detection systems that can accomplish both high accuracy and real-time performance under realistic UAV restrictions, in addition to the findings that have been reviewed. Future studies should concentrate on creating strong yet lightweight models, enhancing tiny item recognition in challenging aerial situations, and guaranteeing flexibility under various operating circumstances.

Furthermore, deploying detection models on UAV platforms with restricted resources would need incorporating sophisticated optimization approaches like quantization, model compression, and effective architecture design. Future research can benefit from more consistent and trustworthy performance comparisons by establishing defined assessment criteria for UAV-based object detection.

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