IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

National Level Conference – AITCON 2K25

Adarsh Institute of Technology & Research Centre, Vita, Maharashtra

Vol. 12, Special Issue 1, March 2025

Enhancing Small Object Detection in UAVs: Challenges, Methods, and Future Directions

Ms. Sangita Akaram Khandekar[1]

Student, Computer Science and Engineering, Ashokrao Mane Group of Institutions, Kolhapur, India[1]

Abstract: This paper discusses the challenges and recent progress in small object detection for Unmanned Aerial Vehicles (UAVs), considering that this is one of the most critical tasks for applications in surveillance, agriculture, and disaster response. Low-resolution UAV-based imagery with scale variance, occlusion, or environmental conditions complicates the task of detecting small objects. The paper briefly reviews the conventional approaches but pays more attention to the modern deep learning methods; multiple-scale feature extraction, attention mechanisms, and anchor box optimization significantly improve detection accuracy. The paper then proceeded to evaluate recently developed state-of-the-art models such as YOLOv5, SSD, Faster R-CNN, and UAV-YOLOv8 for their ability to balance high-precision capabilities with the speed of real-time UAV operation. It identifies future directions toward improving small object detection: lightweight models, multi-modal sensor fusion, and adaptive image resolution. Overall, this paper gives an all-rounded review and identifies some promising avenues of future research into UAV-based small object detection.

Keywords: Feature Pyramid Network, You Only Look Once, Lightweight YOLO, Multi-Scale Feature Fusion Small Object Detection Network

I. INTRODUCTION

UAVs (Unmanned Aerial Vehicles) changed the way so many businesses operate-from surveillance and search-and-rescue missions to agriculture and disaster response. It can take extremely high-resolution aerial photographs and go into inaccessible places, which really make it incredibly useful for today's operations. One of the critical challenges of UAV applications is object detection, especially for small objects that play a very crucial role in identifying targets such as wildlife, crops, and hazardous objects, most especially in cluttered and dynamic environments. For instance, [1] stressed the importance of efficient object detection models in UAV-based remote sensing applications, especially in scenarios with multiple small and occluded objects. Similarly, [2] showed how advanced detection algorithms can significantly improve the accuracy of identifying critical targets in UAV imagery, thus enabling more effective decision-making in real-time situations.

However, detecting small objects in UAV imagery is anything but easy. Several unique challenges, primarily related to the high altitudes at which UAVs operate, varying resolutions of captured images, and complex backgrounds where objects are found, make this task difficult. According to Cheng et al. (2023), small object detection suffers from such problems as scale variance, occlusion, and non-uniform distribution, thereby making traditional techniques of object detection insufficient. Not to mention all these, factors of the environment include fluctuation in lighting conditions, adverse climatic conditions, image blur due to UAV motion among others [3]. This challenge is more serious when objects cover a very small number of pixels, and in such cases, the possibility of false positives and missed detections becomes much higher, according to [4].

Researchers have proposed a wide range of advanced algorithms to counter these problems. [5] Developed the framework MFFSODNet based on multi-scale feature fusion. This helps increase the accuracy in small object detection. [6] Came up with the idea of Dense-YOLO with dense connections alongside modules of multi-scales that minimizes loss of information for better feature extraction. The focus here is an effort to discover such state-of-the-art approaches in order to cast light over the strengths as well as limitations together with promising further research directions aiming towards the strengthening of small object detection in the case of imagery through UAV. Such advancement can ensure high precision and reliability while detecting elements more efficiently using critical UAV application cases, while performing their functionalities better.

II. CHALLENGES IN SMALL OBJECT DETECTION FOR UAVS

Detecting small objects in UAV imagery poses a number of unique challenges that can severely degrade the performance of object detection algorithms. These challenges are caused by resolution, scale variations, occlusion, environmental conditions, and computational constraints. Fig.1 illustrates the core challenges in UAV imagery. Resolution is the most critical problem in the imagery captured by UAVs. Most UAVs capture images at low altitudes. This usually means that small objects occupy a very small number of pixels, which would make them difficult to distinguish. According to [4], a significant amount of fine-grained details is lost during down-sampling when the features are being extracted. Moreover, scale variations arise due to the altitude of the UAV and distance from the target; therefore, objects seem to appear at inconsistent sizes in the image.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

National Level Conference – AITCON 2K25

Adarsh Institute of Technology & Research Centre, Vita, Maharashtra

Vol. 12, Special Issue 1, March 2025

According to [7], this inconsistency in object size makes it difficult to come up with a detection system that operates effectively across different scenarios. To counter these challenges, [8] introduced multi-scale feature fusion techniques, which enable better feature representation across objects of varying sizes, improving the detection of small objects.

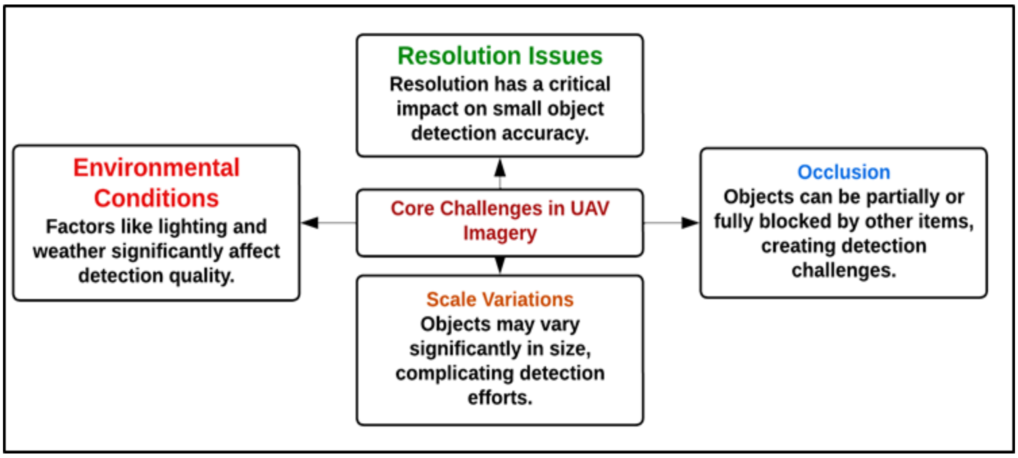

Fig 1: Core Challenges in UAV Imagery

Small objects in the UAV image frequently get occluded by other objects or by other environmental features like trees, buildings, or topography. In cluttered scenarios, dense deployments of objects made [6] comment on the worsening conditions for detection with missed or wrong detections. Where objects overlap complicates the detection, it also introduces difficulties into finding small targets: distinguishing among items that are brought close to one another becomes even tougher. To address this, [9] proposed the use of dense connection modules that enhance the contextual understanding of the scene, thus helping to mitigate the impact of occlusion and reduce detection errors in cluttered environments.

Environmental factors in the form of different lighting settings, such as shadows, overexposure, or glare conditions, and untimely harsh weather conditions during fog or rain make it difficult for the object detector to be of much precision to identify small objects. [10] demonstrated that the above inconsistencies produce too many false negatives because small objects become indistinguishable under them. To boost detection under these challenging conditions, [11] developed spatial context analysis, which incorporates inter-object spatial relationships to strengthen resistance to environmental changes. This is how the detection system can be able to have a better spatial understanding of objects and improve performance under poor conditions.

Another main challenge that UAVs face is their computationally limited nature. They have to process images in real-time with onboard processing power and memory that are significantly limited. Traditional deep learning models have been proven quite accurate but mostly computationally costly and unsuitable for real-time inference on constrained UAV platforms. [1] thus pointed out this limitation as constraining the ability to apply the more complex model on UAV, especially in those critical time-sensitive situations. To overcome the above challenge, [12] developed lightweight architectures including LE-YOLO that would reduce the computational load while offering high detection accuracy. Models like these will promise the possibility of deploying a real-time efficient small object detection system in UAVs.

These multi-faceted challenges of small object detection in UAV imagery include issues such as resolution, scale variation, occlusion due to environmental factors as well as computational issues. The only way to conquer these challenges is to come up with innovative approaches that integrate advanced feature extraction, contextual understanding, and computational efficiency to yield more reliable UAV-based detection systems.

III. METHODS FOR ENHANCING SMALL OBJECT DETECTION

Detection of small objects in UAV imagery has made tremendous progress and developed different approaches to deal with the specific challenges those types of objects present. There are methods used from traditional ways to new age innovations using deep learning, extraction of multi-scale features, as well as using data augmentation. Fig.2 shows evolution of methods for enhancing small object detection in UAV imagery.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

National Level Conference – AITCON 2K25

Adarsh Institute of Technology & Research Centre, Vita, Maharashtra

Vol. 12, Special Issue 1, March 2025

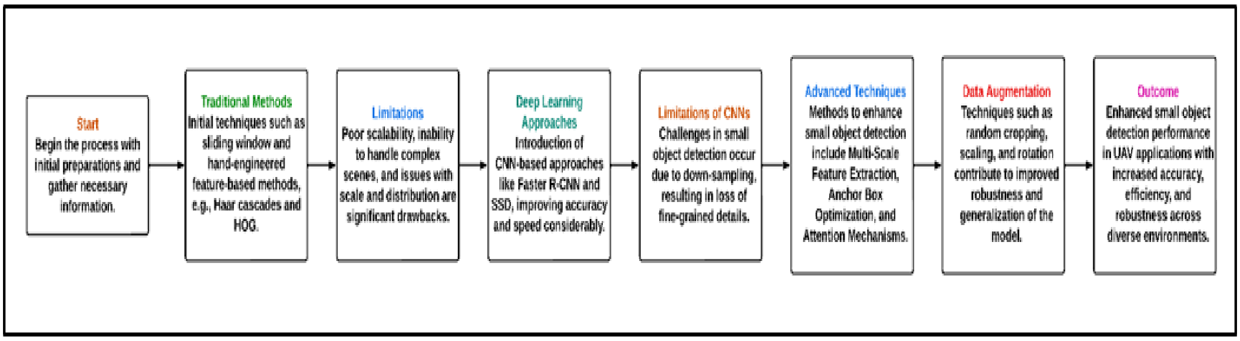

Fig 2: Progression of methods for enhancing small object detection in UAV imagery

In early days of object detection approaches in UAV image processing, usually the sliding windows or hand-engineered feature-based techniques were prevalent. These usually were Haar cascades or Histogram of Oriented Gradients, for example, but they generally suffer from performance and scalability deficiencies on complex large-scale UAV data. According to [7], traditional methods lacked comprehensive sufficiency when detecting small objects, particularly when these were surrounded by very cluttered scenes. Additionally, since these methods would not work appropriately with scale and distribution variations in the object, they only helped limit further use in UAV-based applications.

Convolutional Neural Networks (CNNs) have paved the way by bringing about improvements that help the community overcome most of the conventional approaches' inadequacies. In general, Faster R-CNN and SSD outperformed many models as a benchmark for various object detection tasks in terms of higher accuracy with much faster execution [13]. Nevertheless, in small object detection, CNNs had not completely addressed the limitations. [10] pointed out that deep CNN architectures often led to a loss of fine-grained details necessary for the detection of small objects. Excessive down-sampling in traditional CNN layers reduced spatial resolution, making it harder to detect small objects in UAV imagery.

Researchers have developed more sophisticated algorithms that employ multi-scale feature extraction and receptive field expansion to solve these problems. Feature Pyramid Networks, devised by [14], is one of the most important new developments, allowing models to work effectively on objects of many sizes by producing feature pyramids and hence improving detection on a large number of object sizes. Spatial Pyramid Pooling was further proposed for extending receptive fields in Liu et al. 2024 whereby they help hold the highresolution feature maps from multiscaleness into different scales more precisely for objects detection.

Another notable improvement is anchor box optimization. The traditional anchor boxes applied to models, such as YOLO, sometimes fail when dealing with the detection of smaller objects. [15] modified the YOLO-based model by resizing anchor boxes to accommodate smaller object sizes that enhanced localizing precision. Attention mechanisms, such as CBAM, Convolutional Block Attention Module, which [8] utilized, can enable models to pay attention to the most relevant regions of an image. This would result in improved detection accuracy, especially in cluttered backgrounds where small objects may be obscured. Data augmentation techniques that include random cropping, scaling, and rotation in improving detection performance and model robustness have thus been widely adapted. These allow the models to better generalize with a wide scope of scenarios similar to real world conditions. "Data augmentation" said [16] emphasized its importance that improves model robustness and even guarantees that performance does not shift drastically even through the changing lighting situations, weather shifts, and different other environmental settings typical in application using UAVs.

From traditional techniques to advanced deep learning-based approaches, methods for improving small object detection in UAV imagery have evolved. Through multi-scale feature extraction, receptive field expansion, anchor box optimization, and data augmentation, researchers have improved the accuracy and efficiency of small object detection systems to a great extent. Such developments hold much promise for the development of more reliable and real-time detection in UAV-based applications across challenging environments.

IV. RECENT ADVANCES AND STATE-OF-THE-ART MODELS

Very recent breakthroughs in object detection techniques have led to more efficient and accurate models to deal with challenges associated with the small object in UAV imagery. Of the most commonly known models include YOLOv4 and YOLOv5, SSD, Faster R-CNN, along with other tailored architectures, and all of these approaches are directed at improving performance.

The YOLO family has been significantly improved, especially with the latest versions of YOLOv4 and YOLOv5, optimized for small object detection in UAV imagery. The architecture of YOLOv5 is very lightweight and, therefore, is highly adopted since it strikes a good balance between speed and accuracy. More specifically, [16] further developed the UAV-YOLOv8 model with an emphasis on multi-scale feature fusion and attention mechanisms that will contribute to better small object detection. Another variant was LC-YOLO, an adaptation of YOLOv5, proposed by [17].

The adaptation is a lightweight model with its focus on including attention mechanisms, cross-layer optimizations, and achieves superior detection rates, especially of small targets for real-time use in UAV.

Single Shot MultiBox Detectors (SSD) remains a relevant model for UAV-based small object detection. [10] added a feature pyramid with the scaling-based deconvolution that results in recovering fine-grained features needed for detecting small objects. Improved accuracy with low computational cost results in SSD being an excellent candidate for real-time UAV operations where computational resources may be limited. Faster R-CNN, an efficient deep learning architecture for object detection, also evolved to respond to the demands of small object detection in UAV images. [18] proposed a feature fusion technique driven by spatial cognition within the architecture of Faster R-CNN for enhancing the feature extraction performance for small objects in cluttered UAV scenes. The inclusion of refined Region Proposal Networks (RPNs) and multi-scale strategies further enhanced the model's ability to detect objects of varying sizes, making it more accurate in complex environments, although at the cost of higher computational demand.

Specialized models, such as RetinaNet and multi-scale Feature Pyramid Networks (FPN), have been tailored specifically for UAV applications. [20] have shown how optimized feature aggregation through an FPN-based model led to the effectiveness in the detection of tiny UAV targets, especially when conditions become tough. The developed models specifically take into consideration the constraints and requirements of the operations in the context of UAV. They are designed to be perfect for complex, dynamic environments. The performance of these models is usually evaluated on a combination of accuracy, speed, and computational efficiency. In this regard, models such as UAV-YOLOv8 and LC-YOLO based on YOLOv5 are distinguished for their high speed and lightweight design, which make them especially appropriate for real-time UAV operations in which processing speed is critical. On the other hand, while methods based on Faster R-CNN and SSD are computationally heavier, they do well in cases where higher accuracy is required, especially in complex or cluttered environments, as shown by [10], [18].

The latest developments in small object detection for UAV imagery have led to a variety of models with different strengths. While UAV-YOLOv8 and LC-YOLO variants deliver real-time performance with good accuracy, more computationally expensive models such as Faster R-CNN and SSD are capable of achieving exceptional accuracy in more challenging scenarios. These developments open up more reliable and efficient UAV-based detection systems in diverse operational environments.

V. SUMMARY AND FUTURE DIRECTIONS IN ENHANCING SMALL OBJECT DETECTION FOR UAVS

The detection of small objects in UAV images is still among the many challenges involved, given that detection may be affected by the resolution or change in scale, occlusion, environmental conditions, and computational constraints. Researchers have made great strides with leading-edge algorithms addressing some of the above issues, especially through deep learning models, multi-scale feature extraction, and attention mechanisms. [1] highlighted the need for efficient object detection models in UAV-based remote sensing applications, especially with regard to small and occluded targets. [6] also presented that dense connection models such as Dense-YOLO improve the precision of small object detection by minimizing information loss. Challenges continue to be how the real-time performance can be maintained on the resources of UAV platforms, which is seen according to Yue et al., in 2024 by proposing lighter models like LE-YOLO to compensate for computational requirements.

More recent breakthroughs in this field are, for instance UAV-YOLOv8 and LC-YOLO models that brought the integration of light architecture with multiple scale feature fusion and attention, thereby maintaining efficiency while gaining utmost accuracy [16], [17]. On the contrary, Faster R-CNN and SSD models are more computationally expensive but have better performance in high-precision environments and can be improved by multi-scale strategies and spatial cognition-driven feature fusion [10], [18].

TABLE I KEY REFERENCES AND CONTRIBUTIONS

Paper	Key Contribution	Focus Area
[1]	Emphasized efficient object detection models for remote sensing.	UAV-based remote sensing, small objects
[6]	Introduced Dense-YOLO with dense connections and multi-scale modules.	Small object detection, dense environments
[21]	Addressed scale variance, occlusion, and non-uniform distribution.	Small object detection challenges
[3]	Examined the impact of environmental factors like lighting and weather.	Environmental effects on detection
[11]	Investigated the issue of missed detections due to small objects occupying few pixels.	Missed detections, image resolution
[5]	Proposed MFFSODNet for multi-scale feature fusion.	Multi-scale feature fusion for small object detection
[8]	Implemented multi-scale feature fusion for varying object sizes.	Multi-scale feature extraction

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

National Level Conference – AITCON 2K25

Adarsh Institute of Technology & Research Centre, Vita, Maharashtra

Vol. 12, Special Issue 1, March 2025

[7]	Discussed challenges due to scale variations in UAV imagery.	Scale variance in small object detection
[9]	Proposed dense connection modules to address occlusion and clutter.	Occlusion and clutter challenges
[11]	Introduced spatial context analysis to improve environmental resilience.	Environmental robustness
[12]	Proposed lightweight architectures like LE-YOLO for real-time detection.	Computational constraints, real-time systems
[16]	Developed UAV-YOLOv8 with multi-scale feature fusion and attention mechanisms.	Lightweight models for real-time detection
[17]	Introduced LC-YOLO for superior small target detection in UAV imagery.	Real-time UAV applications
[10]	Enhanced SSD with feature pyramids and scaling-based deconvolution.	SSD enhancements for fine-grained detection
[18]	Applied spatial cognition-driven feature fusion in Faster R-CNN.	Multi-scale strategies in small object detection
[12]	Developed FPN-based models optimized for UAV target detection.	FPN for UAV target detection

The Table 1 summarizes the contribution of the works referenced, demonstrating different techniques and approaches to achieve improved small object detection in UAV imagery. For future research, it is highly recommended that all these advanced techniques be integrated into real-time, resource-efficient UAV systems in a manner where remaining challenges would include improving the robustness to cluttered environments and optimizing the models for operational conditions. Further research into hybrid models that incorporate the best of lightweight and heavy architectures, as well as more effective data augmentation strategies, will be necessary to further enhance small object detection capabilities in UAVs.

A. Future Directions

1. Create computer vision models aimed at effectively detecting small objects in real-time with UAV images.
2. Increase detection precision of dense small objects surrounded by noisy backgrounds.
3. Explore multi-sensor integration to ascertain challenge-friendly detection under harsh climatic and environmental conditions.
4. Examine image resolution control strategies for efficient feature extraction in various heights and distances.
5. Utilize transfer learning to enhance the performance of the model on a diverse range of UAV tasks and a different geographic area.

VI. CONCLUSION

The paper evaluated the challenges and methodologies for detecting small objects based on the resolution limitations and scale variability and occlusion and environmental conditions in UAV images. The focus was to explain and compare traditional methods of detection with modern deep learning approaches like feature extraction, anchor box optimization, and end-to-end-based attention mechanisms integration, all resulting in an improvement in the accuracy of object detection. Key models such as YOLOv5, SSD, and Faster R-CNN, among others, especially the UAV-specific frameworks such as UAV-YOLOv8, have very promising performance with real-time and high-accuracy detection. Important future directions, such as building lightweight models that can run very fast on limited UAV platforms, and enhancing small, dense objects' detection capabilities, were also discussed in the paper. Overall, the paper provides an overall overview of state-of-the-art techniques and highlights pathways for further research to ensure more efficient and reliable UAV-based object detection systems.

REFERENCES

[1]. Y. Kong, X. Shang, and S. Jia, “Drone-DETR: Efficient small object detection for remote sensing image using enhanced RT-DETR model,” Sensors, vol. 24, no. 17, p. 5496, 2024.

[2]. A. Evain et al., “Improving the efficiency of 3D monocular object detection and tracking for road and railway smart mobility,” Sensors, vol. 23, no. 6, p. 3197, 2023.

[3]. X. Li, Y. Wei, J. Li, W. Duan, X. Zhang, and Y. Huang, “Improved YOLOv7 Algorithm for Small Object Detection in Unmanned Aerial Vehicle Image Scenarios,” Applied Sciences, vol. 14, no. 4, p. 1664, 2024.

[4]. Y. Liu, F. Yang, and P. Hu, “Small-object detection in UAV-captured images via multi-branch parallel feature pyramid networks,” IEEE access, vol. 8, pp. 145740–145750, 2020.

[5]. L. Jiang et al., “MFFSODNet: Multi-Scale Feature Fusion Small Object Detection Network for UAV Aerial Images,” IEEE Trans Instrum Meas, 2024.

[6]. Y. Zhou and C. Pang, “Dense-YOLO: Improving Object detection Accuracy for Small Targets in UAV Perspective,” in 2023 3rd International Conference on Electronic Information Engineering and Computer Communication (EIECC), 2023, pp. 625–632.

[7]. D. Han, H. Zhang, S. Wang, W. Chai, H. Zhou, and F. Zhou, “Small Objects Recognition by Exploiting an Improved YOLOv5 Algorithm on the UAV Platform,” in 2023 International Conference on Ubiquitous Communication (Ucom), 2023, pp. 193–198.

[8]. J. Zhang, G. Wan, M. Jiang, G. Lu, X. Tao, and Z. Huang, “Small object detection in UAV image based on improved YOLOv5,” Systems Science & Control Engineering, vol. 11, no. 1, p. 2247082, 2023.

[9]. R. Baidya and H. Jeong, “Yolov5 with convmixer prediction heads for precise object detection in drone imagery,” Sensors, vol. 22, no. 21, p. 8424, 2022.

[10]. X. Liang, J. Zhang, L. Zhuo, Y. Li, and Q. Tian, “Small object detection in unmanned aerial vehicle images using feature fusion and scaling-based single shot detector with spatial context analysis,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 6, pp. 1758–1770, 2019.

[11]. Z. Liu, X. Gao, Y. Wan, J. Wang, and H. Lyu, “An improved YOLOv5 method for small object detection in UAV capture scenes,” IEEE Access, vol. 11, pp. 14365–14374, 2023.

[12]. M. Yue, L. Zhang, J. Huang, and H. Zhang, “Lightweight and efficient tiny-object detection based on improved YOLOv8n for UAV aerial images,” Drones, vol. 8, no. 7, p. 276, 2024.

[13]. J. Yang, H. Yang, F. Wang, and X. Chen, “A modified YOLOv5 for object detection in UAV-captured scenarios,” in 2022 IEEE International Conference on Networking, Sensing and Control (ICNSC), 2022, pp. 1–6.

[14]. T. Gao, M. Wushouer, and G. Tuerhong, “Small object detection method based on improved YOLOv5,” in 2022 International Conference on Virtual Reality, Human-Computer Interaction and Artificial Intelligence (VRHCIAI), 2022, pp. 144–149.

[15]. Y. Yang, W. Zhou, J. Yang, and J. Chen, “Improvement of Small Object Detection Algorithm Based on YOLOv8n in Drone Scene,” in 2024 6th International Conference on Communications, Information System and Computer Engineering (CISCE), 2024, pp. 1175–1180.

[16]. G. Wang, Y. Chen, P. An, H. Hong, J. Hu, and T. Huang, “UAV-YOLOv8: A small-object-detection model based on improved YOLOv8 for UAV aerial photography scenarios,” Sensors, vol. 23, no. 16, p. 7190, 2023.

[17]. M. Cui et al., “LC-YOLO: A lightweight model with efficient utilization of limited detail features for small object detection,” Applied Sciences, vol. 13, no. 5, p. 3174, 2023.

[18]. J. Yu, H. Gao, J. Sun, D. Zhou, and Z. Ju, “Spatial cognition-driven deep learning for car detection in unmanned aerial vehicle imagery,” IEEE Trans Cogn Dev Syst, vol. 14, no. 4, pp. 1574–1583, 2021.

[19]. X. Zhai, Z. Huang, T. Li, H. Liu, and S. Wang, “YOLO-Drone: an optimized YOLOv8 network for tiny UAV object detection,” Electronics (Basel), vol. 12, no. 17, p. 3664, 2023.

[20]. Y. Yang, X. Gao, Y. Wang, and S. Song, “VAMYOLOX: An accurate and efficient object detection algorithm based on visual attention mechanism for UAV optical sensors,” IEEE Sens J, vol. 23, no. 11, pp. 11139–11155, 2022.

[21]. G. Cheng, Z. Shao, Q. Cheng, and H. Luo, “Small Object Detection on Drone-view Images from Multiple UAVs Combination,” in 2023 30th International Conference on Geoinformatics, 2023, pp. 1–7.

.

© IARJSET This work is licensed under a Creative Commons Attribution 4.0 International License