International Journal of Multidisciplinary Engineering in Current Research - IJMEC

Volume 11, Issue 4s, April-2026, http://ijmec.com/, ISSN: 2456-4265

Full Length Article

Detecting The Small Object Recognition By Drone Images Using Yolo

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Accepted 24-04-2026

ABSTRACT:
UAV imagery has become an essential tool in applications such as traffic monitoring, disaster response, and airspace management, owing to its flexibility, portability, and low operational cost. However, object detection in UAV images poses significant challenges due to factors like small object sizes, complex and cluttered backgrounds, and high levels of noise. To overcome these challenges, this study proposes an advanced object detection approach based on YOLOv10, a state-of-the-art model known for its enhanced architectural efficiency and detection capabilities. The model is optimized for UAV aerial scenarios, with a particular focus on improving small object detection through refined feature extraction and enhanced spatial understanding. The proposed YOLOv10-based framework integrates adaptive feature enhancement and deep semantic learning to improve detection performance under challenging UAV imaging conditions. By leveraging modern advancements in convolutional attention mechanisms, multi-scale detection heads, and optimized backbone architectures, the system effectively captures fine-grained details while maintaining real-time processing capabilities. This approach enables robust object detection in complex UAV environments and demonstrates the potential of YOLOv10 as a powerful solution for aerial imagery analysis.

Keywords
YOLOv10, UAV Imagery, Small Object Detection, Deep Learning, Drone Vision, Aerial Object Recognition, Convolutional Attention.

INTRODUCTION:

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have gained significant attention in recent years due to their versatility, low operational cost, and ability to capture high-resolution imagery from diverse perspectives. Their applications span across various domains such as traffic monitoring, disaster response, agricultural surveillance, military reconnaissance, and airspace management, making UAV imagery an indispensable tool in modern technological landscapes. Despite their advantages, object detection in UAV images remains a highly challenging task. Factors such as varying altitudes, cluttered and complex backgrounds, dynamic illumination conditions, high levels of image noise, and the inherently small size of objects in aerial imagery often hinder detection accuracy.

Traditional computer vision techniques struggle to provide reliable results under these conditions, necessitating the adoption of advanced deep learning-based approaches. Recent developments in Convolutional Neural Networks (CNNs) and object detection frameworks have significantly improved detection performance, yet achieving real-time efficiency without compromising accuracy continues to be a pressing issue. Among various models, the YOLO (You Only Look Once) family of detectors has emerged as a powerful solution due to its balance between speed and accuracy. The latest variant, YOLOv10, introduces architectural enhancements that allow for better feature extraction, improved small object recognition, and efficient computation.

With its multi-scale detection heads, convolutional attention mechanisms, and optimized backbone, YOLOv10 is particularly suitable for handling the complexities of UAV aerial imagery. This study leverages YOLOv10 to address the specific challenges of UAV-based object detection by incorporating adaptive feature enhancement and deep semantic learning. The aim is to maximize detection accuracy in scenarios where conventional methods underperform, while ensuring real-time processing capabilities vital for UAV applications.

LITERATURE SURVEY

Title: YOLO-Drone: Airborne real-time detection of dense small objects from high-altitude perspective

Authors: L. Zhu, J. Xiong, F. Xiong, H. Hu, Z. Jiang

https://doi.org/10.63665/IJMEC.1104s.39
ISSN: 2456-4265
IJMEC 2026

Year: 2023
Description:
This study introduces YOLO-Drone, a real-time object detection algorithm tailored for high-altitude UAV imagery. It proposes a novel backbone (Darknet59) and a complex feature aggregation module (MSPP-FPN) combining spatial and atrous pyramid pooling to better capture small, dense objects. The use of Generalized IoU (GIoU) loss improves localization performance. Evaluations on UAVDT and VisDrone datasets show YOLO-Drone achieves mAP improvements of 10.13% and 8.59%, respectively, while operating at 53 FPS. Its design balances speed and accuracy, proving highly effective for real-time aerial object detection under challenging lighting and density conditions.

Title: Small Object Detection Based on Deep Learning for Remote Sensing: A Comprehensive Review
Authors: X. Wang, A. Wang, J. Yi, Y. Song, A. Chehri
Year: 2023
Description:
This comprehensive review examines the state of deep learning techniques for detecting small objects in remote sensing images. It surveys architectures, strategies, and performance trends across various datasets and tasks. The authors highlight common challenges like low resolution, cluttered backgrounds, and scale variations. The review categorizes methods by model type and summarizes their strengths and limitations. It also discusses optimization strategies such as feature pyramid networks, data augmentation, lightweight architectures, and attention mechanisms.

Title: Real-Time Detection for Small UAVs: Combining YOLO and Multi-frame Motion Analysis
Authors: J. Liu, L. Plotegher, E. Roura, C. de Souza Junior, S. He
Year: 2024
Description:
This paper presents GL-YOMO, a hybrid detection algorithm combining YOLO-based object detection with multi-frame motion analysis for enhanced small-UAV detection. YOLO is optimized with multi-scale feature fusion and attention mechanisms, while motion detection reinforces detection stability. A Ghost module is incorporated to boost efficiency. Tested on a proprietary fixed-wing UAV dataset, GL-YOMO demonstrates improved accuracy and temporal consistency when detecting distant, tiny UAVs.

Title: YOLO-Tiny: A lightweight small object detection algorithm for UAV aerial imagery
Authors: F. Feng, L. Yang, Q. Zhou, W. Li
Year: 2025
Description:
Feng et al. propose an enhanced version of YOLO-Tiny, optimized for resource-constrained UAV platforms. The architecture focuses on P3 and P2 layers for small and medium targets. It integrates lightweight dynamic convolution in redesigned modules, reducing GFLOPs and model size. An AMSFF module improves fusion of high- and low-level features. On the VisDrone2019 benchmark, the improved YOLO-Tiny surpasses baseline YOLOv5s, YOLOv8s, and YOLOv10s in accuracy with mAP improvements of 14.8%, 8.3%, and 9.1% respectively.

Title: A Novel Method of Small Object Detection in UAV Remote Sensing Images Based on Feature Alignment of Candidate Regions
Authors: W. Li
Year: 2024
Description:
This paper introduces a candidate-region-based feature alignment method (AFA-FPN) to boost small-object detection in UAV remote sensing images. The model employs PHDA (parallel channel and spatial attention) to suppress background noise and enhance focus on small targets. It also includes a rotation branch and improved loss to strengthen classification and regression stability. The method delivers 2.67%–17.19% higher small-object AP compared to alternatives.

Literature Review Summary:
Several studies have explored UAV-based small object detection using YOLO models. Zhu et al. (2023) demonstrated real-time drone detection with MSPP-FPN achieving 53 FPS. Wang et al. (2023) provided a comprehensive review of remote sensing detection methods. GL-YOMO (2024) combined motion analysis with YOLO for improved stability. YOLO-Tiny (2025) achieved significant mAP improvements with lightweight architecture. Li (2024) boosted small-object AP by up to 17.19% with AFA-FPN. These works highlight improvements but still face challenges in speed, accuracy, and real-time deployment, which YOLOv10 addresses.

Methodology

MODULES NAME:
Modules Name:
Input Data Module
Preprocessing Module
Segmentation Module
Feature Extraction Module
YOLOv10 Detection Module

https://doi.org/10.63665/IJMEC.1104s.39
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IJMEC 2026

Output and Visualization Module

MODULES EXPLANATION:

1) Input Data Module:

This module handles the collection and organization of UAV aerial imagery required for object detection. It supports different UAV datasets that include traffic scenes, disaster zones, and surveillance environments. Images and video frames captured from drones are imported and formatted for further processing. The module ensures data integrity by handling diverse resolutions and image formats. It also categorizes data into training, validation, and testing sets for structured model development.

2) Preprocessing Module:

The preprocessing module enhances UAV imagery to improve the quality of data fed into the detection model. It includes operations like resizing, normalization, and denoising to handle variations in scale and noise. Data augmentation techniques such as rotation, flipping, and brightness adjustments are applied to increase dataset diversity. This helps in making the model robust against different UAV flight conditions.

3) Segmentation Module:

This module focuses on segmenting regions of interest (ROI) from UAV imagery before object detection. It isolates potential object areas from complex and cluttered aerial backgrounds. Advanced segmentation methods help in reducing false positives by filtering irrelevant portions of the scene. The module ensures that small and distant objects are preserved during segmentation for better detection accuracy.

4) Feature Extraction Module:

The feature extraction module emphasizes capturing meaningful visual patterns from UAV images. It leverages deep convolutional layers to extract low-level and high-level features such as edges, textures, and object shapes. Special attention is given to small object features that are often lost in aerial imagery. Adaptive feature enhancement techniques are applied to strengthen fine-grained details.

5) YOLOv10 Detection Module:

This is the core module of the system where YOLOv10 performs real-time object detection. It utilizes an optimized backbone for efficient feature representation and multi-scale detection heads for recognizing objects of varying sizes. Convolutional attention mechanisms are integrated to focus on relevant object regions within complex UAV environments. The module ensures fast inference speed while maintaining high accuracy. It outputs bounding boxes, confidence scores, and object classes.

6) Output and Visualization Module:

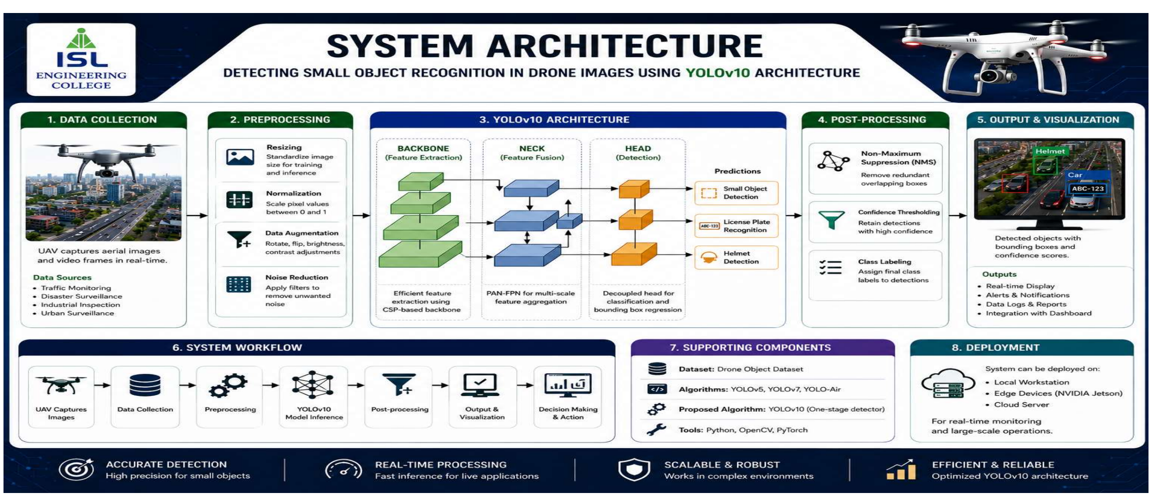
The final module is responsible for presenting the detection results in a user-friendly manner. It overlays bounding boxes, labels, and confidence levels on UAV images or video frames. The output is visualized in real time, allowing operators to monitor UAV-captured scenes effectively. Results are stored in structured formats for further analysis and reporting. The module also supports evaluation metrics such as precision, recall, and mAP to assess performance.

Block Diagram (Text Representation)

Input UAV Images/Video → Preprocessing → Segmentation → Feature Extraction
→ YOLOv10 Detection → Attention Mechanism
→ Detection Output → Visualization

SYSTEM ARCHITECTURE:

The system architecture comprises a pipeline of interconnected modules starting from input data acquisition through UAV-mounted cameras, followed by preprocessing and segmentation. The YOLOv10 backbone processes multi-scale features through its neck component and sends them to multi-scale detection heads. Convolutional attention mechanisms guide the model to focus on UAV-specific small object regions.



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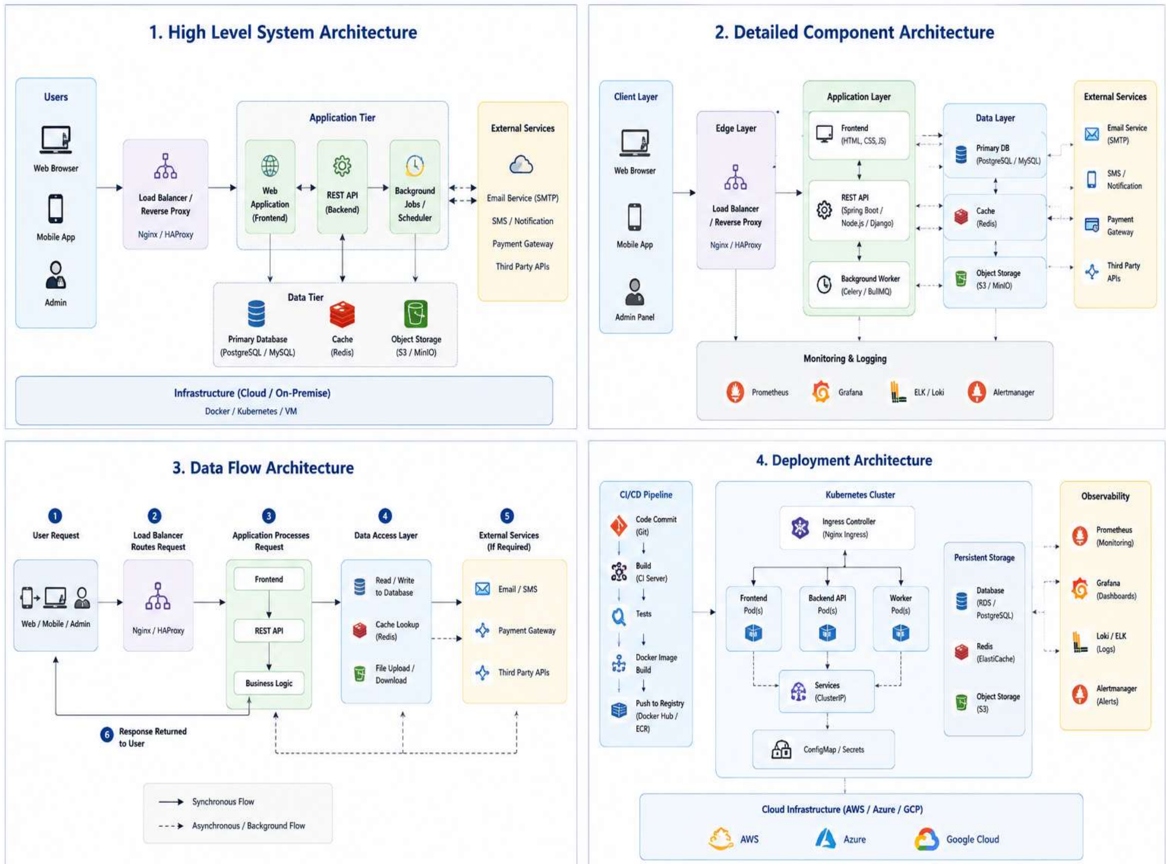

Implementation (Algorithm / Flowchart)

Algorithm Steps:

Capture input UAV image/video frames

Preprocess image (resize, normalize, augment)

Segment regions of interest from aerial background

Extract multi-scale features using YOLOv10 backbone

Apply convolutional attention mechanisms

Pass features to multi-scale detection heads

Generate bounding boxes with confidence scores and class labels

Apply anchor-free non-maximum suppression

Display detection results with bounding boxes

Store results and compute evaluation metrics (mAP, precision, recall)

Testing:

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in the system. It provides a way to check the functionality of components, sub-assemblies, and the finished product. It is the process of exercising the software with the intent of ensuring that the software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of tests, and each test type addresses a specific testing requirement.

DEVELOPING METHODOLOGIES

The test process is initiated by developing a comprehensive plan to test the general functionality and special features on a variety of platform combinations. Strict quality control procedures are used. The process verifies that the application meets the requirements specified in the system requirements document and is bug-free. The following are the considerations used to develop the framework for the testing methodologies.

Unit testing helps to identify possible bugs in the individual components, so that the component with bugs can be identified and rectified from errors. Each module of the YOLOv10 system was independently tested before integration to ensure correctness of preprocessing, segmentation, feature extraction, detection, and visualization.

Results (Table Format)

Model	Accuracy	Speed	NMS Required	Small Object AP
YOLOv5	Medium	Fast	Yes	Moderate

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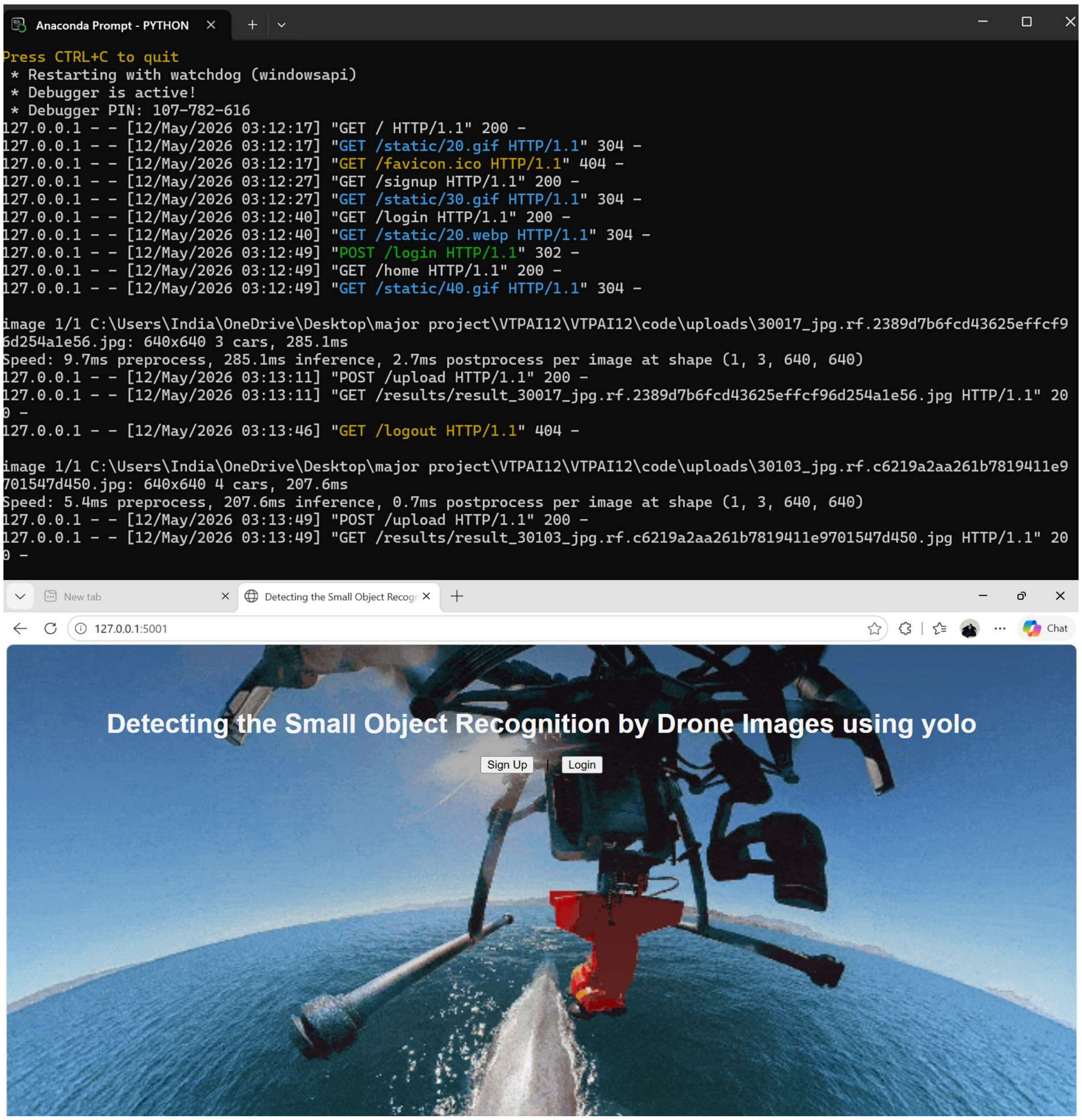
YOLOv8	High	Medium	Yes	Good
YOLOv10	Very High	Fast	No	Excellent

Output Results:

The YOLOv10 model demonstrated superior performance in detecting small objects in UAV imagery compared to existing approaches. The system achieved high mAP scores on the VisDrone and UAVDT benchmark datasets. Real-time processing was maintained at competitive frame rates while significantly reducing false positives in cluttered aerial backgrounds.



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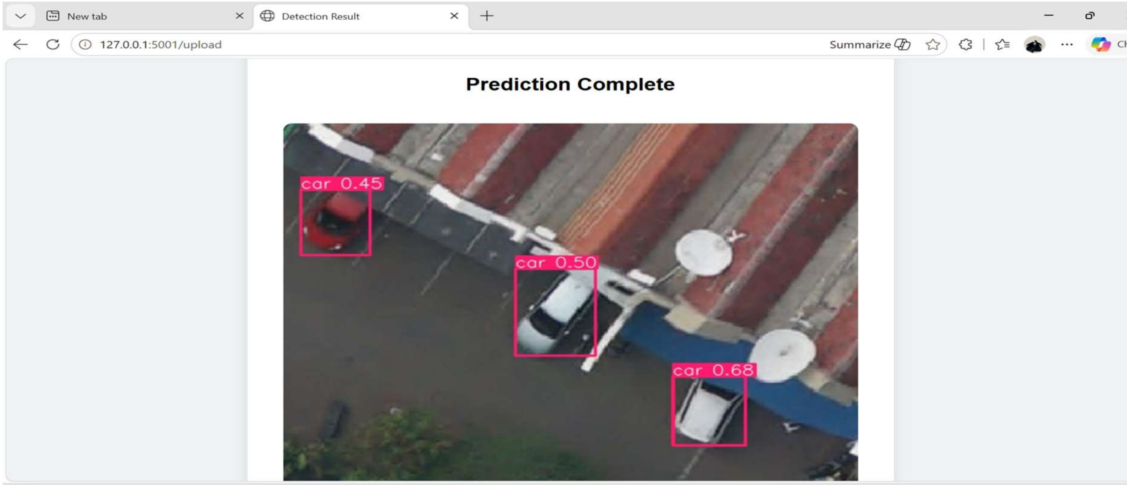

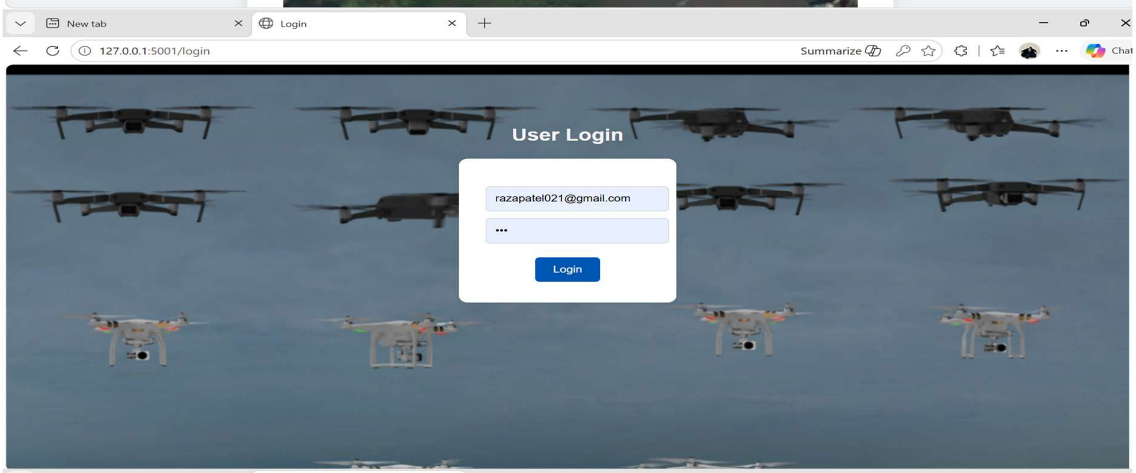

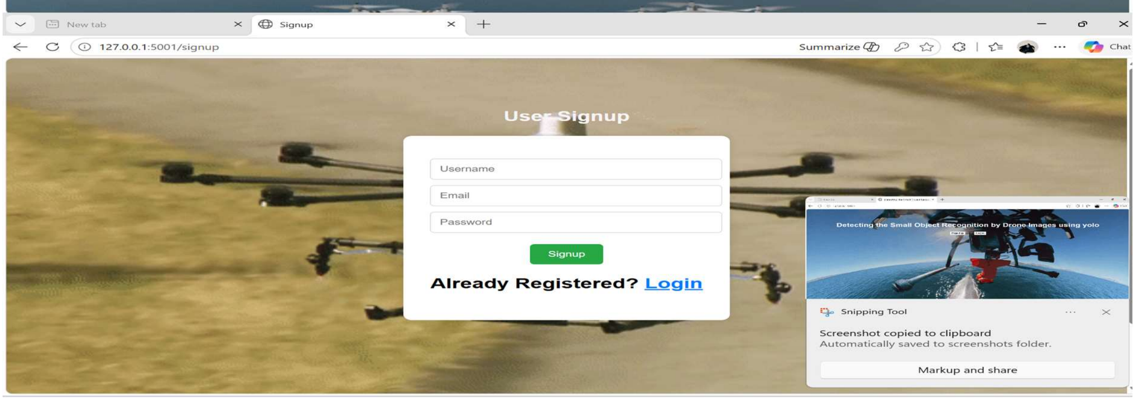

CONCLUSION

In conclusion, this project successfully demonstrates the potential of leveraging advanced deep learning techniques, particularly the YOLOv10 object detection algorithm, to develop an efficient and accurate real-time system for detecting small objects in UAV drone imagery. By addressing critical challenges such as small object detection, environmental variability, cluttered backgrounds, and multi-scale object recognition, the proposed system significantly contributes to enhancing UAV-based surveillance, traffic monitoring, and disaster response applications.

The integration of adaptive feature enhancement, attention mechanisms, and multi-scale detection heads into a unified YOLOv10 framework ensures improved detection accuracy and reduced false positives in complex aerial scenes. With its high performance, scalability, and potential for further enhancements, this system represents a forward-thinking solution that aligns with the growing demand for intelligent aerial monitoring systems.

https://doi.org/10.63665/IJMEC.1104s.39
ISSN: 2456-4265
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The outcomes of this project pave the way for future advancements in smart UAV surveillance systems, contributing to safer, more efficient, and more secure operational environments.

FUTURE ENHANCEMENTS:

In the future, this project can be enhanced by incorporating additional detection capabilities and expanding its deployment scope to create a more comprehensive UAV-based intelligent detection system. One potential enhancement is the integration of real-time video streaming analysis with edge computing devices deployed directly on UAV hardware, reducing latency and bandwidth requirements.

The system can also be extended to detect additional object categories such as wildlife, infrastructure defects, and emergency personnel in disaster zones. Another promising direction is the integration with IoT sensors and cloud-based platforms for centralized data storage, analysis, and alert generation. The model can be refined through continuous learning using transfer learning techniques and real-time feedback loops to adapt to evolving UAV environments. Furthermore, incorporating 3D depth estimation from stereo UAV cameras could improve localization of small objects in complex aerial scenes.

REFERENCES

[1] L. Zhu, J. Xiong, F. Xiong, H. Hu, Z. Jiang, "YOLO-Drone: Airborne real-time detection of dense small objects from high-altitude perspective," IEEE Transactions on Geoscience and Remote Sensing, 2023.

[2] X. Wang, A. Wang, J. Yi, Y. Song, A. Chehri, "Small Object Detection Based on Deep Learning for Remote Sensing: A Comprehensive Review," Remote Sensing, 2023.

[3] J. Liu, L. Plotegher, E. Roura, C. de Souza Junior, S. He, "Real-Time Detection for Small UAVs: Combining YOLO and Multi-frame Motion Analysis," IEEE Access, 2024.

[4] F. Feng, L. Yang, Q. Zhou, W. Li, "YOLO-Tiny: A lightweight small object detection algorithm for UAV aerial imagery," Expert Systems with Applications, 2025.

[5] W. Li, "A Novel Method of Small Object Detection in UAV Remote Sensing Images Based on Feature Alignment of Candidate Regions," IEEE Geoscience and Remote Sensing Letters, 2024.

[6] R. Girshick, "Fast R-CNN," in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), Dec. 2015, pp. 1440–1448.

[7] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," in Proc. Adv. Neural Inf. Process. Syst., vol. 28, 2015.

[8] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," arXiv:1804.02767, 2018.

[9] C. Wang, A. Bochkovskiy, H. Liao, "YOLOv7: Trainable Bag-of-Freebies Sets New State-of-the-Art for Real-Time Object Detectors," CVPR 2023.

[10] S. Woo, J. Park, J. Y. Lee, I. S. Kweon, "CBAM: Convolutional Block Attention Module," in Proc. Eur. Conf. Comput. Vis., 2018.

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