Enabling safe Beyond Visual Line of Sight Drone Operations of Sight Drone Operations Through AI-Powered Object Detection

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***Abstract:* As Artificial Intelligence (AI) becomes a powerful force within the technological field it is being integrated into all fields. As AI improves, optimizing it for everyday life is beneficial for the further development of technology. In this paper, we present our research findings and literature on adversarial examples and object detection. This research builds upon the previous work by investigating and optimizing an unmanned aircraft to be flown with the aid of Artificial Intelligence. We started with classifying and training AI to recognize certain objects on YOLOv11 custom trained models. Then a follow-up using the custom trained model with live drone footage to test the accuracy of the model evaluating how it can be utilized in Beyond Visual Line of Sight (BVLOS). Through this exploration it demonstrates the future of using unmanned aircrafts with support from machine learning.**

Keywords: Artificial Intelligence (AI), Object detection, Unmanned Aerial Systems (UAS), Machine learning, YOLO, Beyond VIsual Line of Sight (BVLOS), Aviation Safety

I. Introduction

As Unmanned Aerial Systems (UAS), or better known as drones, become more prominent in the different fields of business by growing from military to commercial activities they have become popular in different operations. They are used for intelligence surveillance, agriculture, delivery, and public safety. The increasing integration of unmanned aircraft systems (UAS) into the national airspace presents significant challenges for regulatory agencies such as the Federal Aviation Administration (FAA) and the U.S. Government Accountability Office (GAO). This issue is pressing to ensure the safe innovations of drone technology and applications.

Current FAA regulations require drone pilots to maintain a visual line of sight (VLOS) during flight operations. This requirement enforces a direct communication with the pilot and the drone unaided by other devices. Which limits the range, flexibility, and scalability of commercial drone applications, such as delivery services, aerial view inspections, and surveillance. Human visual observers are also constrained by distance, environmental conditions, and inconsistent detection accuracy; the previously stated missions would be impossible to conduct.

As demand for Beyond Visual Line of Sight (BVLOS) operations increases, there is a growing need for automated and reliable detection systems that can enhance airspace safety while reducing reliance on human observers. However, BVLOS operations are only permitted through strict regulations and a waiver process that requires risk assessments, documentation, and other safety measures for a secure flight.

II. YOLOv11 technology and AI integration in Aviation

You Only Look Once (YOLO) is a a real time object detection in computer vision. YOLO processes the entire image in a single evaluation. This architecture allows for YOLO to have fast object detection and accuracy for real-time applications such as autonomous drone operations and aerial surveillance.

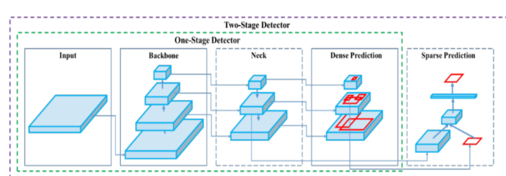

Fig 1. Shows the inner workings of the YOLO model

YOLOv11 is the newest improvement of the previous versions with faster and more accurate detection labelling These improvements include enhancements to the backbone when working with the models spatial information and network structure (Zhao & Zhu, 2025), which is beneficial for identifying distant aircrafts. The integration of the AI-powered object detection is a big step for autonomous flight operations. YOLO could be trained to recognize objects that are relevant for aviation safety such as obstacles, landing zones, wild-life, and hazards. THere can be an early object detection system that effectively sends warnings to the operators.

III. Purpose

The Digital Visual Observer (DiVO) project seeks to develop a safer and more scalable solution for Beyond Visual Line of Sight drones. By integrating real-time video detection systems from drone footage. This addresses challenges by leveraging artificial intelligence–powered sensing technologies, such as YOLOv11, to detect airborne targets from the ground. This research builds upon existing studies in intelligent visual surveillance and distributed multi-camera systems (Remagnino et al., 2004) and applies these concepts to modern drone operations. By enhancing detection capabilities through automation, DiVO aims to support safer and more scalable BVLOS flight operations.

This system would be able to maintain a vigilant observation without getting fatigued and with proper training it could eventually be at the level of accuracy as the human eye.

A key objective is the deployment and optimization of a dual-mode sensor system that utilizes IP cameras to identify aircraft in real time. Additionally, the project seeks to train and refine AI models to enhance their ability to accurately detect airplanes and, eventually, other objects within shared airspace.

IV. Importance of the Research

By providing early alerts to drone pilots regarding nearby aircraft, the DIVO system aims to significantly increase airspace safety. The ability to conduct BVLOS flight operations is critical for drone applications that can boost the economy and lead to social benefit.

V. Regulatory and Operational Barriers

This research is significant because it directly supports the future implementation of BVLOS operations, which are critical for many emerging drone applications. Under current FAA Part 107 regulations, BVLOS flights are heavily restricted unless operators employ additional visual observers or obtain special waivers. These requirements increase operational costs and limit efficiency. The DiVO system offers a technological alternative by reducing the need for multiple human spotters while enhancing situational awareness through automated detection.

If successfully trained and deployed, the DiVO system could be applied across a variety of commercial and public safety sectors, including drone delivery services, emergency response operations, infrastructure inspections, and search and rescue missions. The ability to detect aircraft from the ground before they are visible to a human pilot would significantly reduce the risk of midair collisions and support the safe integration of drones into congested airspace. As emphasized by the GAO, improving detection and monitoring technologies is a critical component of modernizing the national airspace system (U.S. GAO, 2023).

VI. Methods

The DiVO project employed a pre-built artificial intelligence model known as YOLO (You Only Look Once) for object detection. YOLO is widely recognized in computer vision research for its ability to perform real-time object detection with high efficiency (Faizan, 2022). The research process began with the development of a comprehensive dataset that included drone footage collected during daily flight operations, a set of 3,000 airplane images, and 200 images of cars to introduce additional variation during training. Using Roboflow, we created bounding boxes and applied labels to each image, allowing the AI model to learn object shapes, sizes, and spatial features more effectively.

Fig 2. Roboflow labeling and bounding boxes

Following dataset preparation, the YOLO model was trained and refined using multiple training sessions to improve detection accuracy. To simulate real-world operational conditions, a live-object detection pipeline was developed using an IP camera. Previous research has shown that IP camera systems are effective for real-time detection tasks, supporting their use in surveillance and monitoring applications (Transportation Research Procedia, n.d.). Finally, the trained model's performance was evaluated by comparing its detection accuracy against that of an untrained baseline YOLO model.

VII. Findings

The study produced several important findings. Most notably, the trained AI model demonstrated significantly improved performance compared to the untrained version, accurately detecting aircraft in real time. Aircraft identification was consistent and reliable, confirming YOLO's effectiveness for airborne detection tasks. However, the model performed poorly when attempting to detect people, particularly from the higher altitudes typical of drone footage. This limitation highlights the need for additional training data and model refinement. I believe that having additional photos and height differences would help improve the AI training it.

Another challenge encountered during the study was the limited availability of IP camera footage, which restricted the evaluation of real-world conditions for the dual-sensor system. Aircraft were consistently classified under the label "0," which was standard across the dataset. Overall, these findings align with prior research indicating that AI-driven and multi-camera surveillance systems can significantly improve detection accuracy when supported by robust and diverse datasets (Remagnino et al., 2004).

VIII. Results

The results of the DiVO project demonstrate that the AI-powered detection system can successfully identify airplanes with a high degree of accuracy. The customized training dataset substantially improved performance when compared to the baseline YOLO model, confirming the importance of targeted data preparation. While the system shows readiness for further testing and operational evaluation, additional data is required to improve detection of people and other ground-level objects. Despite these limitations, the results indicate strong potential for real-world deployment, particularly in scenarios that require early aircraft detection to ensure flight safety.

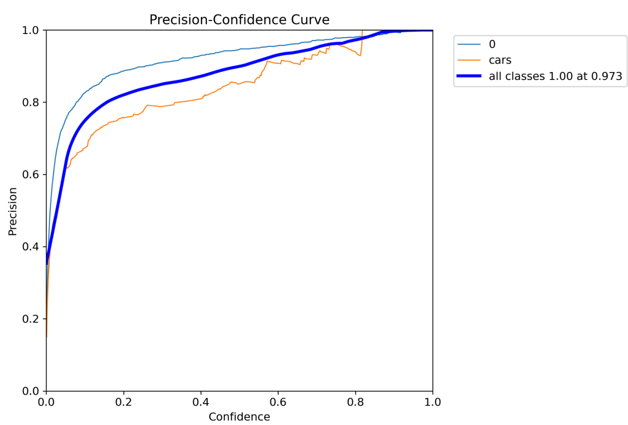

Fig 3. Confidence Curve

In figure 3 this graph shows the relationship between the confidence in the model and how accurate it was. This graph shows that when the model is very confident it is close to 97% correct at labelling. While at a 75% confidence, the model maintained a precision above a 90% for aircraft detection. This further proves that the detection accuracy is at a balanced level of sensitivity and accuracy.

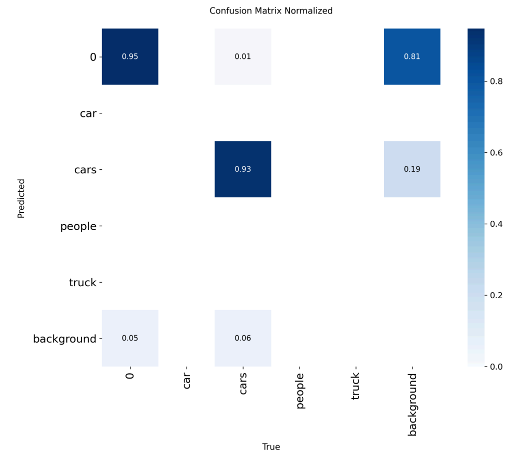

Fig 4. Confusion Matrix Chart

The confusion matrix revealed a strong performance for aircraft detection, with a model achieving 95% accuracy in correctly identifying aircraft (class 0) and there was a 1% misclassification as cars. Car detection performed well by showing a 93% accuracy. However, the matrix showed that there was an absence of people being detected from a high altitude.

IX. Challenges/Limitations

While BVLOS can improve the efficiency of operations while also increasing the capacity of flights it has some challenges. While AI can be integrated into UAVs there needs to be a "motion planner" to reduce the probability of collisions (Elmokadem & Savkin, 2021). This means that the UAVS need to gain a sense of situational awareness, which could take hours of research and technological advancements. To improve planning there have been methods such as sensor based methods, which can lead to poor paths or make the situation worse (Javier Antich Tobaruela & Alberto Gago Rodríguez, 2017). These methods were thought of in the past, but there are other methods like Reinenforcement Learning(RL method which is known for its "flexibility and distributed characteristics" (Wu et al., 2025). A lack of planning or using the wrong method to integrate into UAVs can lead to horrible situations for betterment of using autonomous UAVs within the airspace in the future. Through

X. Future Work

Future development of the DiVO project will focus on expanding the dataset by incorporating additional drone footage, particularly images of people captured at varying distances and altitudes. These efforts will focus on addressing current weaknesses, expanding capabilities, and moving to a more diverse dataset. Increasing environmental diversity in the training data by including different weather conditions and lighting scenarios will further enhance model robustness. Training for different weather will give the operations a higher success rate. Additional IP camera footage will also be collected to improve evaluation of real-world performance.

Beyond technical improvements, the model may be integrated into public safety applications such as search and rescue operations, emergency response missions, and disaster assessment efforts. These future enhancements align with broader industry goals and FAA initiatives aimed at the safe and efficient integration of unmanned aircraft into the national airspace (U.S. GAO, 2023).

XI. Conclusion

The DiVO project demonstrates that AI-powered detection systems have the potential to significantly enhance the safety and scalability of drone operations. By combining YOLO-based object detection with real-time ground camera systems, the project provides a practical pathway toward enabling BVLOS operations while remaining aligned with FAA safety requirements. The trained model outperforms baseline AI detection and shows strong readiness for operational testing. Although further improvements are needed—particularly in detecting people—the DiVO project represents a meaningful advancement toward smarter, safer drone integration within the national airspace.

References

Comparison of Vehicle Detection Techniques applied to IP Camera Video Feeds for use in Intelligent Transport Systems. (n.d.). Transportation Research Procedia, 45, 971–978. https://doi.org/10.1016/j.trpro.2020.02.069

Elmokadem, T., & Savkin, A. V. (2021). Towards Fully Autonomous UAVs: A Survey. Sensors, 21(18), 6223. https://doi.org/10.3390/s21186223

Faizan, M. (2022, April 15). Roboflow. Red Buffer. https://medium.com/red-buffer/roboflow-d4e8c4b52515

Javier Antich Tobaruela, & Alberto Gago Rodríguez. (2017). Reactive navigation in extremely dense and highly intricate environments. PLoS One, 12(12), e0189008–e0189008. https://doi.org/10.1371/journal.pone.0189008

Murat, A. A., & Kiran, M. S. (2025). A comprehensive review on YOLO versions for object detection. Engineering Science and Technology, an International Journal, 70(2215-0986), 102161. https://doi.org/10.1016/j.jestch.2025.102161

Remagnino, P., Shihab, A. I., & Jones, G. A. (2004). Distributed intelligence for multi-camera visual surveillance. Pattern Recognition, 37(4), 675–689. https://doi.org/10.1016/j.patcog.2003.09.017

Small unmanned aircraft systems (UAS) regulations (part 107). (n.d.). Federal Aviation Administration. Retrieved December 2, 2025, from https://www.faa.gov/newsroom/small-unmanned-aircraft-systems-uas-regulations-part-107

U.S. Government Accountability Office. (n.d.). Drones: FAA should improve its approach to integrating drones into the national airspace system. U.S. GAO. Retrieved December 2, 2025, from https://www.gao.gov/products/gao-23-105189

Wu, Y., Chen, W., Peng, L., Zhang, W., Wang, M., & Wang, G. (2025). Autonomous decision-making method for UAV formations with dynamically switchable targets for open environments. Aerospace Science and Technology, 168(1270-9638), 111048. https://doi.org/10.1016/j.ast.2025.111048

Zhao, Q., & Zhu, J. (2025). An Improved YOLOv11 architecture with multi-scale attention and spatial fusion for fine-grained residual detection. Results in Engineering, 27(2590-1230), 107061. https://doi.org/10.1016/j.rineng.2025.107061