Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871

Vol. 7, No. 3, June 2026, Page. 2734-2745
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5661

Artificial Intelligence-Based Aircraft Detection for Enhanced Aviation Safety and Air Traffic Management

Astika Ayuningtyas[*1], Saomi Novelia Gunawan[2], Puspa Ira Dewi Candra Wulan[3], Rully Medianto[4], Sri Winiarti[5], Aris Rakhmadi[6]

[1,2]Departement of Informatics, Adisutjipto Institute of Aerospace Technology, DI Yogyakarta, Indonesia
[3]Departement of Computer Science and Information Engineering, National Taiwan University of Science and Technology, Taiwan
[4]Departement of Aerospace Engineering, Adisutjipto Institute of Aerospace Technology, DI Yogyakarta, Indonesia
[5]Departement of Informatics, Universitas Ahmad Dahlan, DI Yogyakarta, Indonesia
[6]Departement of Informatics Engineering, Universitas Muhammadiyah Surakarta, Jawa Tengah, Indonesia

Email: [1]astika@itda.ac.id

Received : Jan 29, 2026; Revised : Feb 2, 2026; Accepted : Feb 2, 2026; Published : Jun 15, 2026

Abstract

The rapid growth of international air traffic has made maintaining aviation safety and managing air traffic efficiently increasingly complex, particularly in identifying aircraft in constantly changing airspace. Traditional monitoring systems such as radar and Automatic Dependent Surveillance-Broadcast (ADS-B) have limitations in operating at low altitudes, in adverse weather, and in overcrowded environments, which can reduce the ability to understand surrounding conditions. This research proposes an artificial intelligence-based visual detection system aimed at enhancing real-time aircraft identification and improving air traffic monitoring. The system uses a YOLO-based deep learning model enhanced with a special attention mechanism and data augmentation to increase accuracy, flexibility, and operational resilience. The dataset used covers various flight situations, such as variations in light, viewing angles, and background complexity, to train the model. The model's test results show that it can correctly identify 95.24% of passenger planes, 92.4% of blimps, and 90% of fighter planes. The average overall precision (mAP) is over 90%. This system is also capable of real-time inference with precision and recall consistently above 85% under various conditions. Compared with conventional vision-based detection methods, this system demonstrates superior localization capabilities and robustness, making it suitable for use in real-world flight surveillance and air traffic management. In conclusion, this AI-based framework provides a practical and scalable solution that can improve flight safety and promote smarter air traffic management.

Keywords : *Aviation Safety, Computer Vision, Deep Learning, Manned Aircraft Detection.*

1. INTRODUCTION

The swift growth of worldwide aviation operations has heightened the necessity for dependable and flexible monitoring systems to guarantee aviation safety and effective air traffic management [1], [2], [3]. With the growing congestion in contemporary airspace, especially at lower and medium altitudes, the precise detection of manned aircraft in real time is crucial for ensuring situational awareness and mitigating operational risks [3], [4], [5], [6], [7], [8]. Traditional monitoring technologies, including primary radar and Automatic Dependent Surveillance–Broadcast (ADS-B), have been essential in overseeing air traffic [9], [10]. Nonetheless, these systems can face a decline in performance due to unfavorable weather conditions, signal obstruction caused by terrain, reliance on infrastructure,

Vol. 7, No. 3, June 2026, Page. 2734-2745
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5661

or restricted coverage in remote and intricate environments [9], [11]. The identified constraints drive the investigation of alternative detection methods that could improve resilience and adaptability in aircraft monitoring [12]. Recent advancements in computer vision and deep learning have resulted in notable enhancements in object detection across multiple application areas, such as autonomous driving, maritime monitoring, and aerial surveillance [13], [14], [15], [16], [17]. Vision-based aircraft detection utilizing convolutional neural networks (CNNs) has shown encouraging outcomes, especially with the rise of one-stage detectors like the You Only Look Once (YOLO) family, which provides a beneficial equilibrium between detection precision and real-time efficiency [14], [18], [19], [20], [21], [22], [23], [24].

Several investigations have utilized YOLO-based models for the detection of aircraft or drones [25], [26], [27], [28], [29], [30], [31], [32]. Nonetheless, numerous current methods face limitations due to restricted or uniform datasets, diminished resilience in diverse lighting and background scenarios, or an absence of design improvements suited for intricate airspace settings. Furthermore, although attention mechanisms have demonstrated their efficacy in enhancing feature representation across various object detection tasks [33], [34], [35], [36], [37], their comprehensive application for detecting manned aircraft in real-world aviation scenarios has not been thoroughly investigated. This study introduces a framework for aircraft detection utilizing artificial intelligence, aimed at improving aviation safety and optimizing air traffic management. The uniqueness of this study is found in the combination of an attention-enhanced YOLO architecture with specialized data augmentation techniques designed for practical aviation contexts. This work shifts the focus from merely assessing baseline detection performance to highlighting the importance of robustness, adaptability, and operational relevance in various environmental conditions. This study validates the proposed model using a custom-curated dataset that captures realistic variations in illumination, altitude, viewing angles, and background complexity. The findings illustrate that vision-based AI can effectively function as a practical and scalable complementary solution for intelligent airspace surveillance systems.

2. METHOD

This study employs an experimental design to create and assess a framework for aircraft detection based on artificial intelligence, with the goal of improving aviation safety and air traffic management. The workflow involves acquiring and preparing datasets, designing model architectures, training and optimizing, and conducting systematic performance evaluations. An approach utilizing deep learning for object detection is implemented, emphasizing real-time performance and resilience across various operational scenarios. The overall methodology is crafted to guarantee reproducibility and scientific validity, adhering to best practices typically employed in the fields of computer vision and aviation surveillance [16], [38], [39], [40], [41], [42].

2.1. Dataset Acquisition Preparation

The dataset employed in this study was carefully assembled to accurately represent authentic operational situations involving the detection of manned aircraft. Images were collected from a variety of sources, including publicly available aviation image collections, aerial photography datasets, and images taken manually from both ground-level and elevated viewpoints. The dataset encompasses a wide range of environmental factors, such as differences in lighting, elevation, perspective, aircraft orientation, and background complexity. Each image was subjected to a careful process of manual annotation, utilizing bounding boxes to accurately identify the positions of aircraft, following the recognized standards for labeling in object detection. To enhance the diversity of the dataset and improve the adaptability of the model, a range of thorough data enhancement techniques were employed, including geometric transformations, adjustments to brightness and contrast, resizing of images, and

Vol. 7, No. 3, June 2026, Page. 2734-2745
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5661

alterations to backgrounds. These augmentation strategies are consistent with previous findings that demonstrate improved robustness in vision-based detection systems [43], [44], [45], [46]. The dataset was divided into training, validation, and testing subsets using an 80:10:10 ratio to ensure an unbiased evaluation of performance.

2.2. Model Architecture and Training Procedure

The suggested detection framework is constructed on a YOLO-based one-stage object detection architecture, chosen for its equilibrium between detection precision and real-time inference ability [47], [48], [49]. To improve feature representation, attention mechanisms were incorporated into the backbone and neck components of the network, enabling the model to highlight significant spatial and channel features pertinent to aircraft detection [35], [50]. Training of the model was carried out through supervised learning utilizing annotated image data. The loss function includes localization loss, confidence loss, and classification loss, which are optimized through the Adam optimizer utilizing an adaptive learning rate schedule. Training was conducted across several epochs until convergence was achieved, incorporating early stopping to mitigate the risk of overfitting. Hyperparameters were chosen through empirical methods, guided by the performance observed during validation. The assessment of performance was conducted utilizing established metrics for object detection, such as precision, recall, mean Average Precision (mAP), and inference speed quantified in frames per second (FPS). Comparative experiments were carried out to evaluate the effects of attention integration and data augmentation on detection accuracy and robustness. This evaluation strategy aligns with established benchmarking practices in object detection studies [51], [52].

2.3. Algorithmic Workflow and Detection Procedure

To provide a clear and reproducible description of the proposed aircraft detection framework, the overall research procedure is formalized in an algorithmic workflow. This workflow outlines the sequential steps involved in data preparation, model training, attention integration, and performance evaluation. Representing the methodology in algorithmic form improves transparency and facilitates reproducibility, which are essential requirements in scientific research [53], [54]. The detection process initiates with the acquisition and preprocessing of the dataset, subsequently leading to the initialization of the model utilizing a YOLO-based architecture. Attention modules are subsequently incorporated to improve feature extraction. The model undergoes training through a supervised learning approach and is later assessed with standardized metrics for object detection. The entire process is outlined in the pseudocode at Figure 1.

```
Input:
    D_raw  ← Raw image dataset of manned aircraft
    A      ← Data augmentation techniques
    YOLO   ← Base YOLO detection architecture
    Attn   ← Attention module (e.g., SE, CBAM)
    θ      ← Model parameters
    E      ← Number of training epochs

Output:
    M_trained ← Trained aircraft detection model
    P_eval    ← Performance evaluation metrics
```

Figure 1. Proposed AI-Based Aircraft Detection Framework (part 1)

The proposed algorithm highlights its robustness and real-time performance through the integration of attention-enhanced feature learning and domain-specific data augmentation, as shown in Figure 2. This organized workflow guarantees that the detection framework can effectively generalize across various environmental conditions while preserving computational efficiency.

Vol. 7, No. 3, June 2026, Page. 2734-2745
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5661

```
Begin
    1. Acquire raw aircraft images from multiple sources
    2. Annotate images with bounding boxes for aircraft objects
    3. Apply data augmentation A to generate augmented dataset D_aug
    4. Split D_aug into training, validation, and testing sets

    5. Initialize YOLO-based model architecture
    6. Integrate attention module Attn into backbone and/or neck layers

    7. For epoch = 1 to E do
           a. Load training batch from D_train
           b. Perform forward propagation
           c. Compute total loss (localization, confidence, classification)
           d. Update model parameters θ using optimizer
           e. Validate model using D_val
       End For

    8. Evaluate trained model M_trained on test dataset D_test
    9. Compute performance metrics P_eval (Precision, Recall, mAP, FPS)

    10. Output trained model and evaluation results
End
```

Figure 2. Proposed AI-Based Aircraft Detection Framework (part 2)

The algorithmic design facilitates easy adaptation to various YOLO variants or attention mechanisms, thereby supporting extensibility for future research and deployment scenarios.

3. RESULT

This section presents experimental results of the proposed AI-based aircraft detection model. Insights include quantitative performance measures, category-based detection behavior, and robustness across various visual conditions.

3.1. Model Performance

The trained detection model showed impressive performance after 100 training epochs, as shown at Table 1**.** The quantitative evaluation shows a precision of 0.8847 and a recall of 0.9175, indicating the model's ability to accurately detect aircraft while minimizing both false positives and false negatives. The mean Average Precision (mAP) at an IoU threshold of 0.5 reached 0.9296, reflecting excellent detection accuracy based on common evaluation criteria. In the evaluation using stricter metrics (mAP@0.5:0.95), the model achieved a score of 0.7987, indicating consistent localization performance across different levels of bounding box precision. A deeper analysis of the loss confirms that the model has converged effectively. Box loss, objectness loss, and classification loss showed a steady decrease during training, with final values of 0.0131, 0.0028, and 0.0052, respectively.

Table 1. Evaluation Results

Category	Parameter	Value
Metrics	Precision	0.8847
	Recall	0.9175
	mAP@0.5	0.9296
	mAP@0.5:0.95	0.7987

Table 1. Continued Evaluation Results

Category	Parameter	Value
Validation Loss	Box Loss	0.0131
	Objectness Loss	0.0028
	Class Loss	0.0052

Vol. 7, No. 3, June 2026, Page. 2734-2745
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5661

The validation loss curve also supports this pattern, indicating stability in the learning process and the absence of significant overfitting. Overall, these findings demonstrate the high accuracy and reliability of the proposed model in aircraft detection tasks.

3.2. Detection of Each Class

A detailed evaluation of each category, presented in Figure 3, shows that the model demonstrates excellent performance for most aircraft types. The highest accuracy rate was achieved in the helicopter category, with a true positive rate of 0.97 and a precision of 97%. This impressive performance can be attributed to the helicopter's distinctive visual characteristics, particularly the rotor pattern, which are successfully captured by the more sensitive feature extraction mechanism.

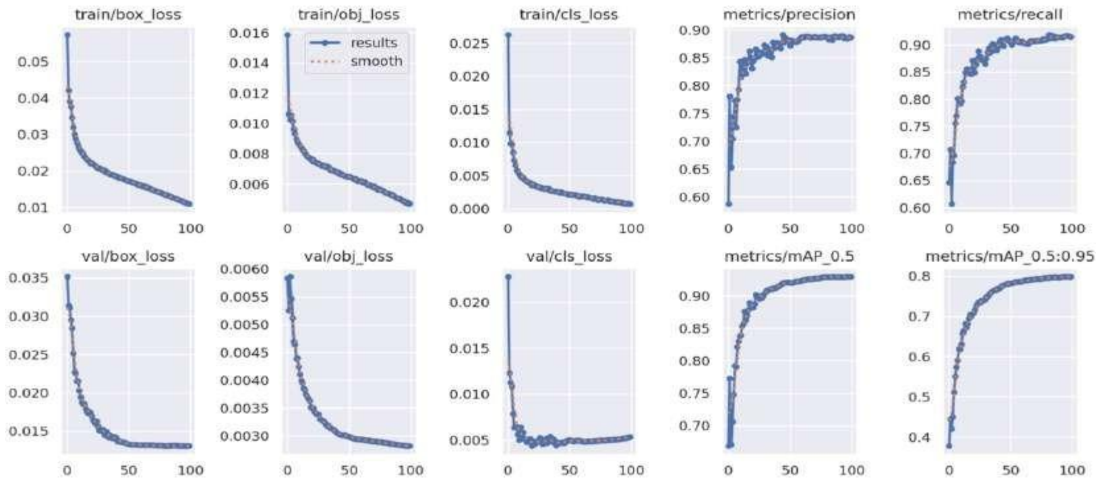

Figure 3. Evaluation Results Graph

3.2.1. Sub-Sub Section

Similarly, the commercial and combat aircraft categories also achieved high precision rates of 95%, indicating strong capabilities in detecting large fixed-wing aircraft. Meanwhile, the hot-air balloon category demonstrated the best overall performance, with a true positive rate of 0.96 and a precision of 96%, reflecting the model's ability to recognize structures with unique envelope shapes. On the other hand, the rocket category performed less well, with a precision of 79% and a higher degree of confusion with the background and the combat aircraft category. These limitations are largely due to the rocket's long shape and its visual similarity to background objects or projectiles at certain viewing angles. Despite these challenges, the model still demonstrated acceptable detection performance, confirming its overall robustness.

3.3. Detection Results on Images and Videos

This detection model was tested using real-world image and video data to determine how well the model performs in real-world situations. Image-based tests were conducted under various lighting conditions, namely morning, afternoon, and night, to assess the model's performance across a range of viewing conditions. The evaluation included 50 static images of five types of aerial objects: a fighter jet (Warplane), a commercial aircraft (Airliner), a rocket (Rocket), a hot-air balloon (Dirigible), and a helicopter (Helicopter). The detection model using YOLO demonstrated high and consistent accuracy across most object classes, with the average accuracy per class shown in Figure 4. These results demonstrate the differences in the model's ability to recognize different object types. Specifically, the hot-air balloon (dirigible) class performed best with an average accuracy above 90%, followed by the commercial aircraft (airliner) and the fighter jet (warplane), which also demonstrated stable performance across various lighting conditions.

Vol. 7, No. 3, June 2026, Page. 2734-2745
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5661

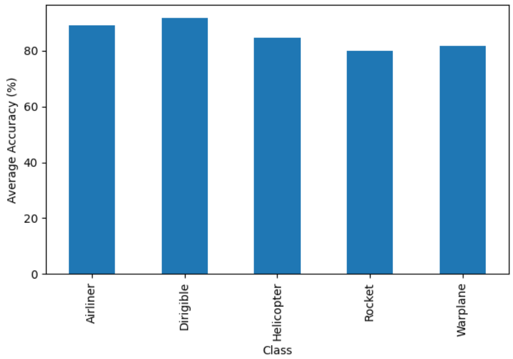

Figure 4. Average detection accuracy on images by class

This suggests that objects with large shapes, distinctive shapes, and contrasting backgrounds are more easily recognized by the model. However, the Rocket class showed the lowest accuracy. This performance decline is caused by several factors, such as differences in object size, extreme viewing angles, and visual similarity between the object and the sky background. These results are consistent with previous studies that found small and elongated objects to be more difficult to detect consistently. The average detection accuracy for the Dirigible class was 92.4% with a standard deviation of 2.5%. For the Airliner and Warplane classes, it was 88.6% and 87.5%, respectively, with small differences. This shows that both classes perform very consistently.

In contrast, the Rocket class showed an average accuracy of 75.3% with a larger standard deviation of 7.1%, indicating instability in detecting small objects and at extreme viewing angles. This analysis is consistent with the results of previous studies, which also found difficulties in detecting small or elongated objects using the YOLO-based detection method [20], [55], [56], [57]. Further testing was conducted on 54 short 720p videos taken from various online platforms to evaluate the system's ability to detect objects in real time. In general, detection performance on videos was slightly worse than on static images due to motion blur, rapid size changes, and partial obstructions encountered during video recording.

The average accuracy results per class are shown in Figure 5. The hot-air balloon (dirigible) class again performed best with the highest accuracy, followed by commercial aircraft (airliner) and helicopters (helicopter). This consistency in results indicates that the model can maintain stable predictions for large, slow-moving objects. In contrast, the Rocket class remains the most challenging, especially in nighttime videos and at extreme shooting angles.

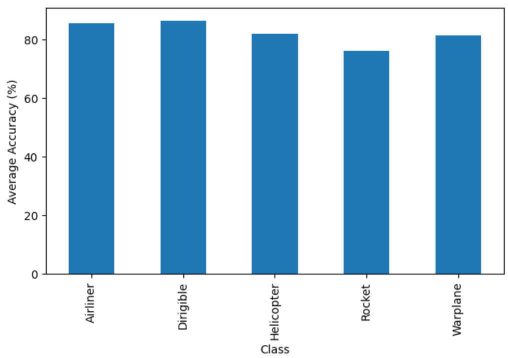

Figure 5. Average detection accuracy on videos by class

Statistically, the average accuracy for videos in the Dirigible class was 89.3% with a standard deviation of 3.2%, while the Airliner and Helicopter classes had average accuracies of 84.7% and 87.4%, respectively. The Rocket class experienced a significant decrease in accuracy, at 76.5% with a standard

Vol. 7, No. 3, June 2026, Page. 2734-2745
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5661

deviation of 7.1%, illustrating the difficulty in detecting small and fast-moving objects in videos. Compared to previous studies evaluating aerial object detection using YOLO, these results demonstrate that the multi-scenario approach in this study is superior in detecting various types of objects under different conditions, both in images and videos [58], [59], [60], [61], [62]. The higher decrease in accuracy in videos, especially for small objects like rockets, indicates that while the YOLO model is highly effective in static image conditions, videos with rapid movement and size changes remain challenges that need to be addressed in the development of future detection systems.

3.4. Confidence Score and Error Analysis

Confidence score analysis offers extra information about the model's ability to detect objects. In general, the model achieved high confidence scores for detecting commercial aircraft (airliners) and fighter aircraft (warplanes), with values of 0.84 and 0.85, respectively. These detections were accompanied by tight bounding boxes and few background elements, indicating high accuracy and confidence in recognizing objects with clear shapes and contrast. However, for helicopter and hot air balloon detection, confidence scores were moderate, ranging from 0.76 to 0.78. While detection results remained accurate, lower scores indicated changes in the object's position or occluded parts, which slightly reduced prediction accuracy. The lowest confidence score was for rockets, with a value of around 0.62. In rocket detection, bounding boxes tended to be wider and the background more visible, suggesting uncertainty in the prediction results, as shown as Table 2.

Table 2. Confidence Score Analysis

Test Sample	Category	Confidence Score	Bounding Box Quality	Rating
air1.jpeg	Airliner	0.84	Tight capture, minimal background	Excellent
hel2.jpeg	Helicopter	0.76	Precise detection, rotor fully detected	Good
war3.jpeg	Warplane	0.85	Perfect alignment with object	Excellent
dir5.jpeg	Dirigible	0.78	Envelope shape detected quite well	Good
roc7.jpeg	Rocket	0.62	Loose bounding box, a lot of noise	Fair

Confusion matrix analysis showed that up to 35% of rocket predictions were incorrectly categorized as background, suggesting that the model needs improvement in detecting small objects or objects with subtle visual characteristics. These findings suggest that future improvements could be made by adding more specific training data or giving greater weight to the rocket class in the training process. This approach could help the model better recognize objects that have similar shapes to the background or small objects that are difficult to detect.

4. DISCUSSIONS

The experimental findings confirm that the proposed YOLO-based framework exhibits robustness and adaptability under various visual conditions, making it competitive with existing aircraft and drone detection research. However, beyond evaluating the effectiveness of the current approach, these results also highlight clear opportunities for further research that could improve real-world aerial surveillance systems. One important area of future research is improving the detection of small objects, particularly long ones and those difficult to see with the naked eye, such as rockets. The observed discrepancy in results suggests that the multi-level feature extraction methods commonly used in YOLO architectures may not be sufficiently effective when dealing with large-scale differences. Future studies could explore more sophisticated feature pyramid designs, transformer-based attention modules, or principal structures that combine CNNs and transformers to enhance more detailed spatial representations without excessively increasing computational costs. Another important research direction concerns the diversity of data types and their levels of verisimilitude. Although this study used real-world images and videos

Vol. 7, No. 3, June 2026, Page. 2734-2745
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5661

under various lighting conditions, the datasets used remain limited by their limited range of occurrences, extreme viewing angles, and adverse weather conditions. Future research should consider using datasets spanning a wide range of domains and at a large scale, including augmenting real-world data with artificial data, simulations based on physical principles, or data-generating models to enrich the training data and improve generalization in rare but safety-critical situations. From an operational perspective, time-based modeling in the video detection process is a very promising development. Current systems process each video frame separately, which can result in inconsistent predictions when motion blur or obscured image areas are present. Using temporal consistency mechanisms, such as lightweight tracking modules or temporal attention, could improve the stability of detection in continuous surveillance applications. Furthermore, research should explore network edge deployments and real-time performance improvements, particularly in resource-constrained environments, such as remote radar stations or airborne surveillance platforms. Model refinement, adaptable inference strategies, and hardware-aware optimizations will increase the likelihood of the proposed system being implemented in real-world air traffic management infrastructure. In summary, while the proposed framework demonstrates good readiness for real-world deployment, future research should focus on improving small object recognition, data scalability, temporal sequence recognition, and implementation efficiency. Addressing these aspects will further strengthen the system's ability to support reliable and intelligent flight surveillance in an increasingly complex airspace environment.

5. CONCLUSION

This research has successfully presented an artificial intelligence-based aircraft detection framework designed to improve aviation safety and support intelligent air traffic management. The system delivers on its promise of providing a robust solution for handling a wide range of environmental conditions and aircraft categories, demonstrating high accuracy in terms of precision (85–95%), recall (85–95%), and mean average precision (mAP) above 90%, while maintaining real-time inference capabilities on 720p video. The system's consistent performance across varying lighting conditions, object scales, and background complexity demonstrates its effectiveness for both static and dynamic video surveillance scenarios. The system can detect objects such as airliners with 92.4% accuracy, warplanes with 95.24% accuracy, and helicopters and dirigibles with average scores of 0.76 to 0.85, demonstrating the model's effectiveness in identifying objects of varying sizes and backgrounds. These findings also highlight the practical relevance of the proposed framework as a complementary surveillance solution to traditional systems such as radar and ADS-B, particularly in situations where infrastructure limitations or environmental factors reduce the reliability of conventional surveillance technologies. Although some object categories, such as rockets, present greater detection challenges due to visual ambiguity and scale variations, with a confidence score of approximately 0.62, the overall system demonstrates strong generalization and operational stability. Looking ahead, this research opens opportunities for further development, particularly in improving detection performance for difficult-to-detect objects through class-specific optimization strategies, dataset expansion, and the integration of temporal information from video sequences. Additional research could also explore the application of this system to edge computing platforms and fusion with non-visual sensor data to further enhance situational awareness. The uniqueness of this research lies in its holistic and operationally oriented approach to aircraft detection, prioritizing robustness, adaptability, and real-time applicability over detection accuracy alone. By combining the enhanced YOLO architecture with attention, domain-specific data augmentation, and comprehensive image and video evaluation, this research offers a scalable and practical solution that contributes to more advanced intelligent flight surveillance and air traffic management systems. Future research is expected to build on these strengths, address existing challenges, and explore further applications in real-world airspace monitoring.

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

ACKNOWLEDGEMENT

Special thanks are extended to the Adisutjipto Institute of Aerospace Technology (ITD Adisutjipto) for its support in this research. Furthermore, I would like to thank all my colleagues who have contributed to the scientific articles of this collaborative research project between ITD Adisutjipto, Universitas Ahmad Dahlan, National Taiwan University of Science and Technology, and Muhammadiyah Surakarta. I look forward to participating in future joint research efforts.

REFERENCES

[1] U. Kale, I. Jankovics, A. Nagy, and D. Rohács, "Towards sustainability in air traffic management," *Sustainability*, vol. 13, no. 10, p. 5451, 2021, https://doi.org/10.3390/su13105451.

[2] F. P. Moreno, V. F. G. Comendador, R. D.-A. Jurado, M. Z. Suárez, D. Janisch, and R. M. A. Valdés, "Methodology of air traffic flow clustering and 3-D prediction of air traffic density in ATC sectors based on machine learning models," *Expert Syst. Appl.*, vol. 223, p. 119897, 2023, https://doi.org/10.1016/j.eswa.2023.119897.

[3] A. Hamissi and A. Dhraief, "A survey on the unmanned aircraft system traffic management," *ACM Comput. Surv.*, vol. 56, no. 3, pp. 1–37, 2023, https://doi.org/10.1145/3617992.

[4] M. K. Singh, N. S. Singha, and V. D. Prabhakar, "Advanced AI-enabled UAV Swarms for Real-time Air Traffic Surveillance," 2026, https://doi.org/10.1108/978-1-80592-062-520251006.

[5] G. Maalouf, K. Jensen, and J. H. Jepsen, "Airspace Situational Awareness: Proposed Airspace Safety Concepts & State-of-the-art Review of UAS Aircraft Detection Technologies," in *International Conference on Unmanned Aircraft Systems*, 2024, https://doi.org/10.1109/icuas60882.2024.10557082.

[6] W. Ahmed, A. Masood, and J. Manzoor, "Towards Secure Air Traffic Surveillance: A Survey on ADS-B Threats, Existing Solutions, and Future Research," *IEEE Open Journal of the Computer Society*, vol. 7, pp. 290–313, 2026, https://doi.org/10.1109/ojcs.2026.3651384.

[7] Y. Chi, J. Nie, L. Zhong, Y. Wang, and D. Delahaye, "A review of situational awareness in air traffic control," *IEEE Access*, vol. 11, pp. 134040–134057, 2023, https://doi.org/10.1109/access.2023.3336415.

[8] W. Li, P. Kearney, J. Zhang, Y. Hsu, and G. Braithwaite, "The analysis of occurrences associated with air traffic volume and air traffic controllers' alertness for fatigue risk management," *Risk analysis*, vol. 41, no. 6, pp. 1004–1018, 2021, https://doi.org/10.1111/risa.13594.

[9] W. Ahmed, A. Masood, and J. Manzoor, "Towards Secure Air Traffic Surveillance: A Survey on ADS-B Threats, Existing Solutions, and Future Research," *IEEE Open Journal of the Computer Society*, vol. 7, pp. 290–313, 2026, https://doi.org/10.1109/ojcs.2026.3651384.

[10] H. A. Khan, H. Khan, S. Ghafoor, and M. A. Khan, "A survey on security of automatic dependent surveillance-broadcast (ADS-B) protocol: Challenges, potential solutions and future directions," *IEEE Communications Surveys & Tutorials*, 2024, https://doi.org/10.1109/comst.2024.3513213.

[11] T. Aliyev and I. Isgandarov, "Analysis of Negative Impacts On Air Traffic Control Radar Systems and Modern Methods for Their Elimination," *International Journal of Aviation Science and Technology*, vol. 6, no. 01, pp. 45–59, 2025, https://doi.org/10.23890/ijast.vm06is01.0105.

[12] Q. U. Ain, A. A. A. Jilani, N. A. Butt, S. U. Rehman, and H. A. Alhulayyil, "Anomaly detection for aviation cyber-physical system: Opportunities and challenges," *IEEE Access*, vol. 12, pp. 175905–175925, 2024, https://doi.org/10.1109/access.2024.3495519.

[13] F. Alamri, "Comprehensive study on object detection for security and surveillance: A concise review," *Multimed. Tools Appl.*, pp. 1–32, 2025, https://doi.org/10.1007/s11042-025-20801-6.

[14] C. P. Ranjith, B. M. Hardas, M. S. K. Mohideen, N. N. Raj, N. R. Robert, and P. Mohan, "Robust deep learning empowered real time object detection for unmanned aerial vehicles-based

surveillance applications," *Journal of Mobile Multimedia*, vol. 19, no. 2, pp. 451–476, 2023, https://doi.org/10.13052/jmm1550-4646.1925.

[15] G. A. Vaidya, "Object Detection In Video Streaming Using Machine Learning And Cnn Techniques.," *Journal of Advanced Zoology*, vol. 45, 2024, https://doi.org/10.53555/jaz.v45is4.4183.

[16] P. Thai, S. Alam, N. Lilith, and B. T. Nguyen, "A computer vision framework using convolutional neural networks for airport-airside surveillance," *Transp. Res. Part C Emerg. Technol.*, vol. 137, p. 103590, 2022, https://doi.org/10.1016/j.trc.2022.103590.

[17] D. K. Pramudito, "Enhancing real-time object detection in autonomous systems using deep learning and computer vision techniques," *The Journal of Academic Science*, vol. 1, no. 6, pp. 788–804, 2024, https://doi.org/10.59613/v3015d10.

[18] L. Du and Y. Wang, "Bi-YOLO: A novel object detection network and dataset for components of China heritage buildings," *Journal of Building Engineering*, p. 110817, 2024, https://doi.org/10.1016/j.jobe.2024.110817.

[19] B. Cheng, B. Wang, Z. Liu, Q. Wang, T. Shen, and Y. Gu, "Airplane symmetry-based convolutional neural network for airplane detection in remote sensing image," 2023, https://doi.org/10.1049/icp.2024.1726.

[20] M. Wang *et al.*, "FE-YOLOv5: Feature enhancement network based on YOLOv5 for small object detection," *J. Vis. Commun. Image Represent.*, vol. 90, p. 103752, 2023, doi: https://doi.org/10.1016/j.jvcir.2023.103752.

[21] C. Xiaoming *et al.*, "An improved algorithm based on YOLOv5 for detecting Ambrosia trifida in UAV images," *Front. Plant Sci.*, vol. 15, May 2024, doi: https://doi.org/10.3389/fpls.2024.1360419.

[22] D. Tian, J. Chen, and X. Wang, "Application research of UAV infrared diagnosis technology in intelligent inspection of substations," *Energy Informatics*, vol. 7, no. 1, Dec. 2024, doi: https://doi.org/10.1186/s42162-024-00364-w.

[23] J. Wang, T. Zhang, and Y. Cheng, "Deep Learning for Object Detection: A Survey.," *Computer Systems Science & Engineering*, vol. 38, no. 2, 2021, doi: https://doi.org/10.1186/s42162-024-00364-w.

[24] M. H. Hamzenejadi and H. Mohseni, "Fine-tuned YOLOv5 for real-time vehicle detection in UAV imagery: Architectural improvements and performance boost," *Expert Syst. Appl.*, vol. 231, p. 120845, 2023, https://doi.org/10.1016/j.eswa.2023.120845.

[25] A. Ayuningtyas, I. Riadi, and A. Yudhana, "Analisis Sistem Deteksi Citra untuk Optimalisasi Pengawasan Lalu Lintas Udara Menggunakan Algoritma YOLOv5," *JISKA (Jurnal Informatika Sunan Kalijaga)*, vol. 10, no. 3, pp. 364–376, Sep. 2025, doi: https://doi.org/10.14421/jiska.2025.10.3.364-376.

[26] A. Ayuningtyas, I. Riadi, and A. Yudhana, "Analisis Sistem Deteksi Citra untuk Optimalisasi Pengawasan Lalu Lintas Udara Menggunakan Algoritma YOLOv5," 2025, https://doi.org/10.14421/jiska.2025.10.3.364-376.

[27] A. Ayuningtyas, I. Riadi, and A. Yudhana, "The Effect of Light Intensity, Camera Pixel Quality, Camera Distance, and Object Altitude on Detection Accuracy in a Real-Time Drone Surveillance System Using YOLOv5," *Journal of Innovation Information Technology and Application (JINITA)*, vol. 7, no. 2, pp. 234–246, Dec. 2025, doi: https:/doi.org/10.35970/jinita.v7i2.2843.

[28] M. Naranjo *et al.*, "Object detection-based system for traffic signs on drone-captured images," *Drones*, vol. 7, no. 2, p. 112, 2023, https://doi.org/10.3390/drones7020112.

[29] J. Sandino, F. Maire, P. Caccetta, C. Sanderson, and F. Gonzalez, "Drone-based autonomous motion planning system for outdoor environments under object detection uncertainty," *Remote Sens. (Basel).*, vol. 13, no. 21, p. 4481, 2021, https://doi.org/10.3390/rs13214481.

[30] X. Zhu, S. Lyu, X. Wang, and Q. Zhao, "TPH-YOLOv5: Improved YOLOv5 based on transformer prediction head for object detection on drone-captured scenarios," in *Proceedings of the IEEE/CVF international conference on computer vision*, 2021, pp. 2778–2788, https://doi.org/10.1109/iccvw54120.2021.00312.

[31] J. Han, R. Cao, A. Brighente, and M. Conti, "Light-YOLOv5: A Lightweight Drone Detector for Resource-Constrained Cameras," *IEEE Internet Things J.*, vol. 11, no. 6, pp. 11046–11057, 2023, https://doi.org/10.1109/jiot.2023.3329221.

[32] S. Singha and B. Aydin, "Automated drone detection using YOLOv4," *Drones*, vol. 5, no. 3, p. 95, 2021, https://doi.org/10.3390/drones5030095.

[33] Q. Zhang, H. Han, F. Li, and Y. Du, "Attention-Aware Based Differentiable Architecture Search Network for Waste Recognition," in *2023 IEEE 13th International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER)*, IEEE, Jul. 2023, pp. 408–412. doi: https://doi.org/10.1109/CYBER59472.2023.10256542.

[34] Anupriya and R. Kumar, "Attention-based Improved YOLOv5 for Effective Waste Detection and Classification System," in *2024 International Conference on Electrical Electronics and Computing Technologies (ICEECT)*, IEEE, Aug. 2024, pp. 1–6. doi: https://doi.org/10.1109/ICEECT61758.2024.10739282.

[35] Z. Cao, C. Fu, J. Ye, B. Li, and Y. Li, "SiamAPN++: Siamese attentional aggregation network for real-time UAV tracking," in *2021 IEEE/RSJ international conference on intelligent robots and systems (IROS)*, IEEE, 2021, pp. 3086–3092, https://doi.org/10.1109/IROS51168.2021.9636309.

[36] D. Yang *et al.*, "An efficient multi-task learning CNN for driver attention monitoring," *Journal of Systems Architecture*, vol. 148, p. 103085, 2024, doi: https://doi.org/10.1016/j.sysarc.2024.103085.

[37] F. S. Alrayes, M. Zakariah, S. U. Amin, Z. I. Khan, and J. S. Alqurni, "CNN Channel Attention Intrusion Detection System Using NSL-KDD Dataset," *Computers, Materials and Continua*, vol. 79, no. 3, pp. 4319–4347, 2024, doi: https://doi.org/10.32604/cmc.2024.050586.

[38] R. Szeliski, *Computer vision: algorithms and applications*. Springer Nature, 2022, https://doi.org/10.1007/978-3-030-34372-9.

[39] M. Farhadmanesh, A. Rashidi, A. K. Subedi, and N. Marković, "A computer vision-based standalone system for automated operational data collection at non-towered airports," *IEEE Access*, 2024, https://doi.org/10.1109/access.2024.3425572.

[40] M. Farhadmanesh, A. Rashidi, and N. Marković, "General aviation aircraft identification at non-towered airports using a two-step computer vision-based approach," *IEEE Access*, vol. 10, pp. 48778–48791, 2022, https://doi.org/10.1109/access.2022.3172963.

[41] K. Man and J. Chahl, "A Review of Synthetic Image Data and Its Use in Computer Vision," *J. Imaging*, vol. 8, no. 11, p. 310, Nov. 2022, doi: https://doi.org/10.3390/jimaging8110310.

[42] I. Shad, Z. Zhang, M. Asim, M. Al-habib, S. Chelloug, and A. El-latif, "Deep learning-based image processing framework for efficient surface litter detection in Computer Vision applications," *J. Radiat. Res. Appl. Sci.*, vol. null, p. null, 2025, doi: https://doi.org/10.1016/j.jrras.2025.101534.

[43] Y. Zhang, H. Zhu, and S. Yu, "Adaptive Data Augmentation for Contrastive Learning," in *ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, IEEE, Jun. 2023, pp. 1–5. doi: https://doi.org/10.1109/ICASSP49357.2023.10095350.

[44] B. Zoph, E. D. Cubuk, G. Ghiasi, T.-Y. Lin, J. Shlens, and Q. V Le, "Learning data augmentation strategies for object detection," in *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXVII 16*, Springer, 2020, pp. 566–583, https://doi.org/10.1007/978-3-030-58583-9_34.

[45] S. Arezoomandan, J. Klohoker, and D. K. Han, "Data Augmentation Pipeline for Enhanced UAV Surveillance," 2025, pp. 366–380. doi: https://doi.org/10.1007/978-3-031-78172-8_24.

[46] A. Mumuni, F. Mumuni, and N. K. Gerrar, "A Survey of Synthetic Data Augmentation Methods in Machine Vision," *Machine Intelligence Research*, vol. 21, no. 5, pp. 831–869, Oct. 2024, doi: https://doi.org/10.1007/s11633-022-1411-7.

[47] G. H. Rishi, P. R. Kumar, N. C. Varshit, and K. Sailaja, "Real-time military aircraft detection using YOLOv5," in *2024 Second International Conference on Data Science and Information System (ICDSIS)*, IEEE, 2024, pp. 1–7, https://doi.org/10.1109/icdsis61070.2024.10594590.

Vol. 7, No. 3, June 2026, Page. 2734-2745
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.3.5661

[48] H. R. Alsanad, A. Z. Sadik, O. N. Ucan, M. Ilyas, and O. Bayat, "YOLO-V3 based real-time drone detection algorithm," *Multimed. Tools Appl.*, vol. 81, no. 18, pp. 26185–26198, 2022, https://doi.org/10.1007/s11042-022-12939-4.

[49] D. J. N. Patel and D. S. B. Patel, "Real-Time Object Detection: A Benchmarking Study of Yolo Versions.," *Journal of Scholastic Engineering Science and Management*, vol. 3, no. 8, pp. 1–6, 2024, doi: https://doi.org/10.47738/jads.v6i2.587.

[50] J. Liu and X. Dai, "Real-time object detection for UAVs images based on improved YOLOv5," in *Third International Conference on Computer Vision and Pattern Analysis (ICCPA 2023)*, SPIE, 2023, pp. 45–51, https://doi.org/10.1117/12.2684359.

[51] G. Cheng *et al.*, "Towards large-scale small object detection: Survey and benchmarks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 45, no. 11, pp. 13467–13488, 2023, https://doi.org/10.1109/tpami.2023.3290594.

[52] W. Chen, J. Luo, F. Zhang, and Z. Tian, "A review of object detection: Datasets, performance evaluation, architecture, applications and current trends," *Multimed. Tools Appl.*, vol. 83, no. 24, pp. 65603–65661, 2024, https://doi.org/10.1007/s11042-023-17949-4.

[53] S. K. Radha, A. Kuehlkamp, and J. Nabrzyski, "Advancing transparency and responsibility in machine learning: The critical role of FAIR principles-A comprehensive review," *ACM Journal on Responsible Computing*, vol. 2, no. 4, pp. 1–38, 2025, https://doi.org/10.1145/3768151.

[54] K. B. Shiferaw, I. Balaur, D. Welter, D. Waltemath, and A. A. Zeleke, "CALIFRAME: a proposed method of calibrating reporting guidelines with FAIR principles to foster reproducibility of AI research in medicine," *JAMIA Open*, vol. 7, no. 4, p. ooae105, 2024, https://doi.org/10.1093/jamiaopen/ooae105.

[55] J. Zhang, Y. Zhang, J. Liu, Y. Lan, and T. Zhang, "Human figure detection in Han portrait stone images via enhanced YOLO-v5," *Herit. Sci.*, vol. 12, no. 1, p. 119, 2024, doi: https://doi.org/10.1186/s40494-024-01232-2.

[56] B. Jiang, H. Jiang, H. Zhang, Q. Zhang, Z. Li, and L. Huang, "4AC-YOLOv5: an improved algorithm for small target face detection," *EURASIP J. Image Video Process.*, vol. 2024, no. 1, Dec. 2024, doi: https://doi.org/10.1186/s13640-024-00625-4.

[57] W. Zhan *et al.*, "An improved Yolov5 real-time detection method for small objects captured by UAV," *Soft comput.*, vol. 26, no. 1, pp. 361–373, 2022, https://doi.org/10.1007/s00500-021-06407-8.

[58] B. Ghari, A. Tourani, A. Shahbahrami, and G. Gaydadjiev, "Pedestrian detection in low-light conditions: A comprehensive survey," *Image Vis. Comput.*, p. 105106, 2024, https://doi.org/10.1016/j.imavis.2024.105106.

[59] M. Krišto, M. Ivasic-Kos, and M. Pobar, "Thermal object detection in difficult weather conditions using YOLO," *IEEE access*, vol. 8, pp. 125459–125476, 2020, doi: https://doi.org/10.1109/access.2020.3007481.

[60] T. Abekoon, H. Sajindra, J. Jayakody, E. Samarakoon, and U. Rathnayake, "Image processing techniques to identify tomato quality under market conditions," *Smart Agricultural Technology*, vol. 7, p. 100433, 2024, doi: https://doi.org/10.1016/j.atech.2024.100433.

[61] H.-K. Jung and G.-S. Choi, "Improved yolov5: Efficient object detection using drone images under various conditions," *Applied Sciences*, vol. 12, no. 14, p. 7255, 2022, https://doi.org/10.3390/app12147255.

[62] Z. Hu, Y. Jing, and G. Wu, "Decision-level fusion detection method of visible and infrared images under low light conditions," *EURASIP J. Adv. Signal Process.*, vol. 2023, no. 1, Dec. 2023, doi: https://doi.org/10.1186/s13634-023-01002-5.