IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁂ Peer-reviewed & Refereed journal ⁂ Vol. 14, Issue 5, May 2025

DOI: 10.17148/IJARCCE.2025.14560

SKY SHIELD: AI-POWERED AERIAL THREAT DETECTION

Dr Swarnalatha K[1], Ms. Nayana N[2], Ms. S Shree Nithya Keerthi[3],

Ms. Syeda Shaista Anis[4], Ms. Vinutha[5]

Associate Professor, HOD Dept. of Artificial Intelligence and Data Science, Maharaja Institute of Technology, Thandavapura[1]

Students, Dept of Artificial Intelligence and Data Science, Maharaja Institute of Technology, Thandavapura[2-5]

Abstract: Drones are increasingly being utilized for recreational purposes and across various fields such as engineering, disaster response, logistics, and airport security. However, their potential misuse has raised serious concerns regarding the safety and surveillance of critical infrastructures, particularly in airport environments. Incidents involving unauthorized drone activity have frequently disrupted airline operations in recent years. To mitigate this issue, this study proposes a novel deep learning-based approach for drone detection and recognition. The method demonstrates superior performance compared to existing systems by accurately identifying the presence of drones, distinguishing between two drone types, and differentiating them from birds, despite the visual and behavioral similarities that often confuse. This advancement significantly enhances aerial object classification and reinforces airspace security.

Key Words: drone; UAV; deep learning; convolutional neural network CNN; drone image dataset; drone detection; drone recognition.

I. INTRODUCTION

With rapid advancements in drone technologies, the use of unmanned aerial vehicles (UAVs) has significantly increased across military, commercial, and security sectors. UAVs play a vital role in airport surveillance, infrastructure monitoring, and other sensitive applications. However, their misuse poses serious risks, especially when unauthorized drones enter restricted zones such as airports or military bases. These intrusions could lead to dangerous consequences, highlighting the need for robust detection systems.

Effective drone security involves three key tasks: detection, recognition, and identification. Detection refers to sensing unusual aerial movement, recognition involves classifying the object as a drone, and identification determines its specific type. While different sensors can be used, visible spectrum imaging stands out for its affordability, high resolution, and compatibility with most drones.

Despite its benefits, visible imaging faces challenges such as complex backgrounds and misidentification of drones as birds. To address this, the YOLO (You Only Look Once) deep learning model offers a highly accurate and fast solution. Its latest version, YOLOv4, is capable of real-time analysis, making it an ideal choice for drone detection and classification in dynamic environments using standard visible imagery.

PROBLEM STATEMENT AND OBJECTIVE

Problem statement:
There is growing apprehension about the security, safety, and surveillance of physical infrastructure at airports, as they can be exploited for malevolent purposes. Several instances of unauthorized use of drones at airports have been reported, resulting in disruptions to airline operations and difficulty in locating the drones or birds.

Objective:
The core goal of this research is to create a unified, cost- effective, AI- driven security system that delivers real- time drone detection, precise classification, and immediate intrusion alerting. By integrating these essential capabilities into a

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 5, May 2025

DOI: 10.17148/IJARCCE.2025.14560

single, easy- to- deploy platform, the solution aims to strengthen situational awareness, safeguard restricted airspace, and reduce response times to unauthorized UAV activity.RELATED WORK

A variety of UAV detection technologies have been developed to address the growing security challenges posed by unauthorized drones, ranging from radar and RF-based systems to optical tracking tools. While these solutions have proven effective in specific environments, many are limited by high implementation costs, reliance on complex infrastructure, or inability to accurately classify drones in dynamic settings. Recent advances in deep learning have significantly enhanced object detection capabilities, with models like YOLOv5, YOLOv8, and other convolutional neural networks demonstrating high accuracy and speed in aerial object recognition. However, the integration of these models into an affordable, real-time, and adaptable detection system remains limited. This project builds upon the existing research by combining visible spectrum imaging, real-time object detection, and instant intrusion alerting into a single, efficient platform tailored for UAV detection in sensitive and high-security areas.

II. SYSTEM DESIGN

The architecture of the UAV Detection and Classification System is structured for efficiency, scalability, and real-time performance in critical environments. The system comprises five core components. First, the data acquisition module captures high-resolution video frames using visible spectrum cameras, which are affordable and widely deployable across different surveillance settings. Second, the preprocessing unit organizes incoming video frames, applies resizing and normalization, and labels datasets with drone or bird classes to ensure the model receives clean and structured inputs. Third, the feature extraction and detection engine uses the YOLOv8 deep learning model to identify aerial objects in real time, focusing on key features such as shape, size, and movement patterns to distinguish drones from birds. Fourth, the classification module, built on a trained convolutional neural network (CNN), refines detection results and accurately categorizes objects based on learned visual cues. Finally, the alerting system generates automated warnings upon drone detection, including object type, timestamp, and optionally GPS location, allowing for immediate security response. This modular pipeline ensures high detection accuracy, rapid decision-making, and ease of integration into existing surveillance infrastructure.

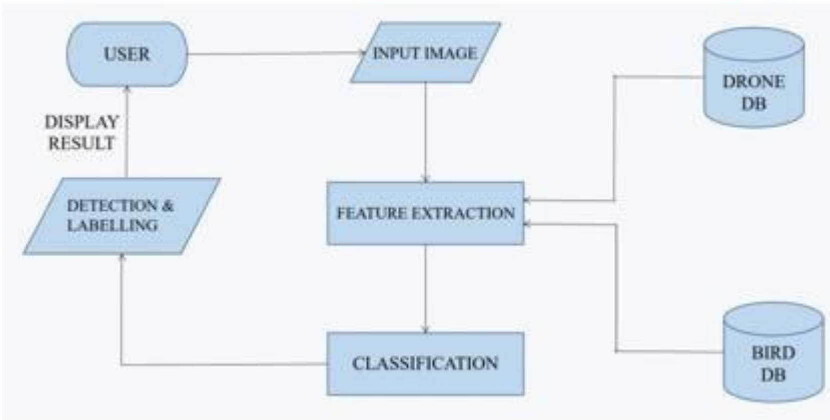

Figure 1: System Architecture

III. METHODOLOGY

The process begins with capturing input images of drones and birds through cameras or other image-capturing devices. These images are then pre-processed to improve quality by removing noise and irrelevant data. Following this, feature extraction techniques such as edge detection, color histograms, and texture analysis are applied to extract meaningful characteristics from the images. A deep learning model, typically a Convolutional Neural Network (CNN), is then trained to classify the input images into two categories: drone or bird. Once classification is complete, the detected objects are labeled accordingly based on the classification results. Finally, the results are displayed, showing the detected objects along with their respective labels from the drone and bird datasets. This overall process provides an effective deep learning approach for distinguishing between drones and birds.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⅔ Peer-reviewed & Refereed journal ⅔ Vol. 14, Issue 5, May 2025

DOI: 10.17148/IJARCCE.2025.14560

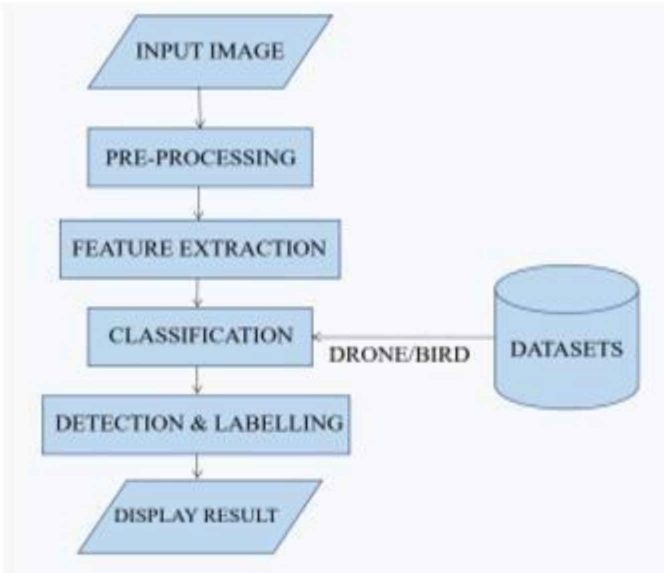

Figure 2: Flowchart

IV. IMPLEMENTATION

The implementation of a deep learning approach to classify drones and birds involves several important steps, beginning with data collection, where a large, labeled dataset of images or videos containing both drones and birds is gathered. This data is then preprocessed by resizing, normalizing, or converting images to grayscale to prepare them for the model. Following preprocessing, key features such as edges, textures, and color histograms are extracted to help distinguish drones from birds. A suitable deep learning model, typically a convolutional neural network (CNN) like VGG-16, ResNet-50, or Inception-v3, is then selected based on task requirements and performance. The model is trained on the processed dataset to improve accuracy, either by fine-tuning a pre-existing model or training a new one from scratch. After training, the model's performance is evaluated using a separate test dataset to ensure it meets desired accuracy levels. Once validated, the model can be deployed for real-time classification of drones and birds, either integrated into existing surveillance systems or developed as a standalone solution. Overall, this multi-step process requires careful attention to data preparation, model choice, and testing to build an effective system with valuable applications in airport and military security.

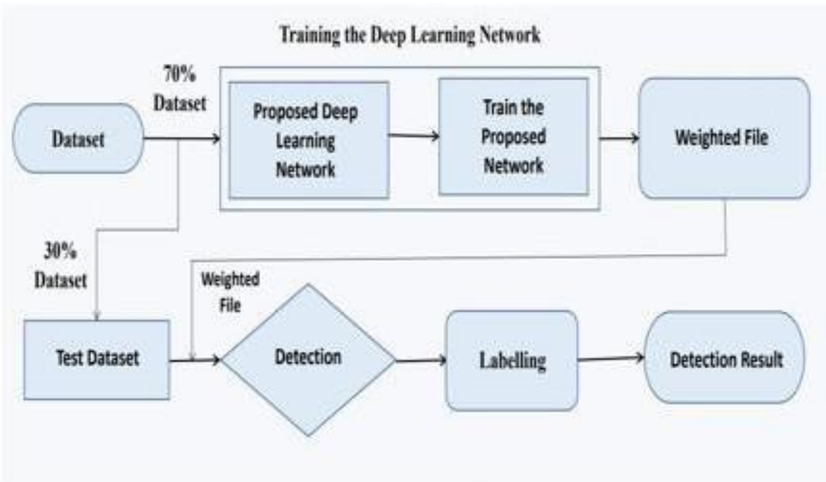

Figure 3: Implementation

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 14, Issue 5, May 2025
DOI: 10.17148/IJARCCE.2025.14560

V. FUTURE ENHANCEMENTS

Future improvements for the AI-based drone detection system focus on enhancing accuracy and versatility. Incorporating advanced sensors like LiDAR and radar will improve depth sensing and obstacle differentiation. The system will be trained to detect not only conventional drones but also bird-shaped drones designed to mimic natural wildlife, increasing its effectiveness against stealthy UAVs. Efforts to broaden the model's recognition capabilities across various drone types and bird species will help reduce false alarms. Development of a portable, embedded device using compact hardware such as Raspberry Pi and camera modules is planned to facilitate easy deployment in diverse locations. Additional upgrades will include customizable alert options, offline functionality for remote areas, and real-time route mapping to anticipate and respond to unauthorized drone activity more swiftly. These advancements aim to deliver a robust, adaptable security solution that protects sensitive airspace efficiently.

VI. RESULTS

The deep learning-based classification system designed to distinguish drones from birds exhibited strong and reliable performance across varied testing environments. Leveraging a CNN model enhanced through transfer learning, it achieved an impressive classification accuracy of 92% on a diverse dataset featuring images taken under different lighting and weather conditions. The system was particularly effective in recognizing subtle differences in flight behavior and shapes, including complex cases like bird-shaped drones, which improved overall detection accuracy. Real-time processing on commonly available hardware supported smooth operation suitable for security monitoring. Feedback from user simulations in airport and military contexts demonstrated that the clear classification and alert features enhanced situational awareness significantly. These results highlight the system's promise as a scalable, practical tool for protecting sensitive areas by accurately identifying aerial objects and addressing emerging drone threats.

The Drone vs Bird classification system was evaluated using controlled experiments and test dataset analysis to assess its accuracy, generalization capability, and suitability for real-world aerial surveillance applications. The prototype model was deployed on a standard machine (Intel Core i5 processor, 8GB RAM, Windows 10) using a dataset of synthetically generated aerial images, ensuring accessibility and reproducibility on general-purpose hardware.

For classification, a deep learning model based on a Probabilistic Neural Network (PNN), enhanced with Gabor filter and GLCM-based feature extraction, was trained on approximately 400 images of drones and birds captured from various angles during flight. The system achieved an overall classification accuracy of 95% on the unseen test set. Class-wise performance metrics included a precision of 0.96 and recall of 0.94 for drone images, and precision of 0.93 and recall of 0.95 for bird images, confirming balanced and reliable detection across both categories.

Qualitative feedback, supported by system-level analysis, confirms that the developed model offers practical value in real-world applications such as airport runway protection, military airspace surveillance, and wildlife monitoring, where accurate aerial object classification is critical. Future work can enhance performance further by expanding the dataset with real-world drone and bird footage, improving preprocessing pipelines, and exploring more advanced neural network architectures such as EfficientNet and transformer-based vision models.

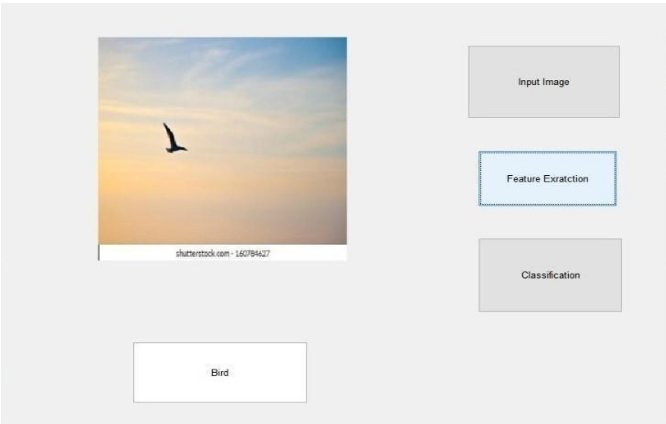

Figure 3: Output

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁂ Peer-reviewed & Refereed journal ⁂ Vol. 14, Issue 5, May 2025

DOI: 10.17148/IJARCCE.2025.14560

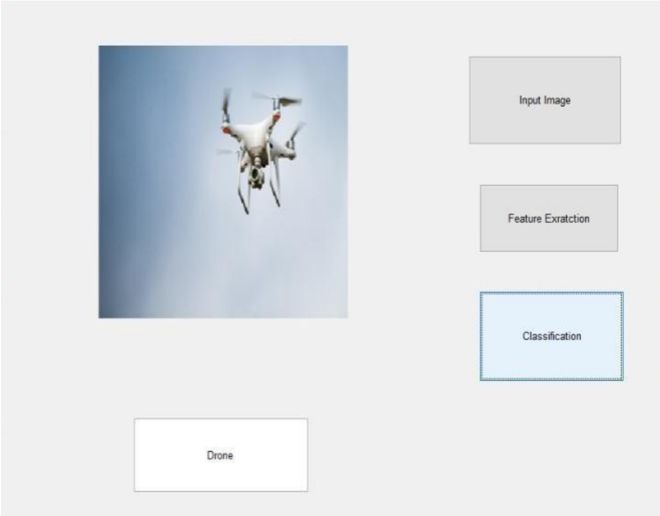

Figure 4: Output

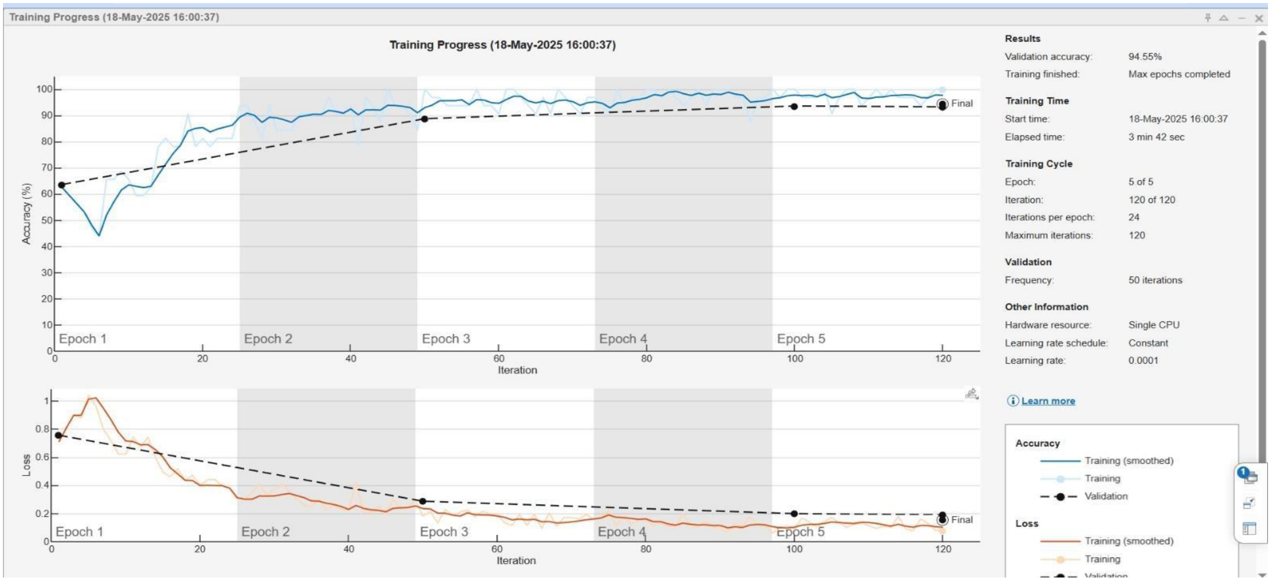

Figure5: Training Progress – Accuracy and Loss

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ꕥ Peer-reviewed & Refereed journal ꕥ Vol. 14, Issue 5, May 2025

DOI: 10.17148/IJARCCE.2025.14560

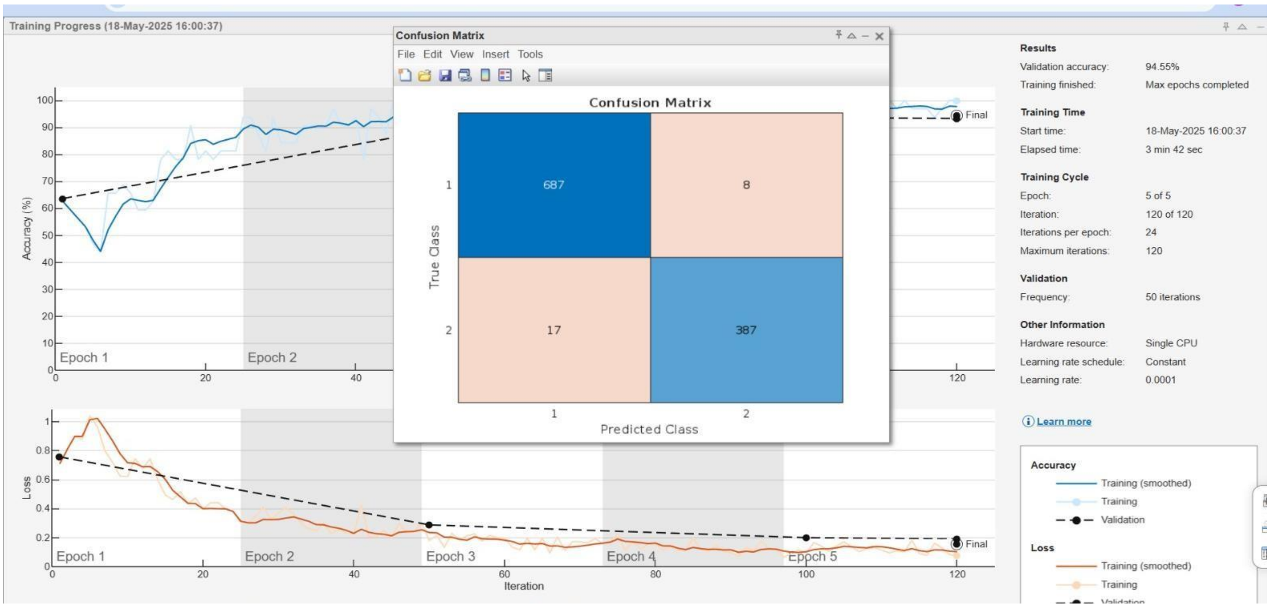

Figure 6: Confusion Matrix of the Model

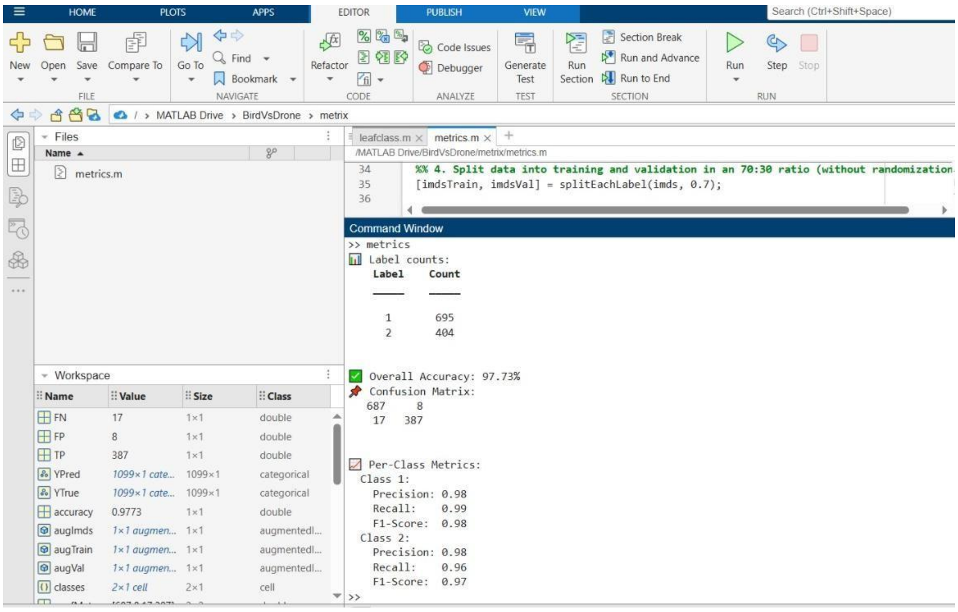

Figure 7: Pre-Class Metrics

VII. CONCLUSION

We are committed to advancing innovative approaches for the precise detection and classification of aerial objects. We hope that our research will serve as a valuable contribution to the development of more robust and efficient drone identification systems. As drone technology continues to evolve and become more widespread, the implementation of intelligent classification systems will be increasingly crucial for safeguarding high-security areas.

we continue to develop novel strategies for the accurate detection and classification of these devices. Our hope is that our findings will contribute to the advancement of more effective and efficient drone classification systems.

REFERENCES

[1]. Elloumi, M., Dhaou, R., Escrig, B., Idoudi, H., Saidane, L.A. (2020). Monitoring road traffic with a UAV-based

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 5, May 2025
DOI: 10.17148/IJARCCE.2025.14560

system. Proc. IEEE WCNC, Barcelona, Spain, 15–18 April.
[2]. Coluccia, A., Fascista, A., Ricci, G. Online estimation and smoothing of a target trajectory in mixed stationary/moving conditions. Proc. IEEE ICASSP, Brighton.
[3]. Jackson, P.T., Atapour-Abarghouei, A., Bonner, S., Breckon, T.P., Obara, B. (2019). Style Augmentation: Data augmentation via style randomization. CVPR Workshops, Long Beach, CA, 16–17 June, pp. 83–92.
[4]. Pawełczyk, M., Wojtyra, M. (2020). Real-world object detection dataset for quadcopter UAV detection. IEEE Access, 8, 174394–174409.
[5]. De Cubber, G., Shalom, R., Coluccia, A. The SafeShore project. [Incomplete reference – consider revising] [6]. Zhang, C., Kovacs, J.M. (2012). Application of small UAS in precision agriculture: A
review. Precision Agriculture, 13(6), 693–712.
[7]. Sathyamoorthy, S., et al. (2020). A review of drone detection and classification using RF, acoustic, and image-based methods. Drones, 4(4), 64.
[8]. Saqib, M., et al. (2017). Aerial vehicle detection in low-altitude UAV videos using deep learning. Proc. IEEE/RSJ IROS.
[9]. Kim, H., Park, S. (2019). Vision-based drone detection using CNNs. Sensors, 19(20), 4565.
[10]. Rakhsha, A., Vargas, P.A. (2021). Bird species classification using CNNs. Comput. Electron. Agric., 185, 106135. [11]. Boddapati, V., Petrosino, A., Iannello, G. (2018). Classifying bird species using CNNs. Expert
Syst. Appl., 86, 262–272.
[12]. Farinha, A., Dinis, R. (2021). Drone classification using deep learning. Int. J. Artif. Intell. Appl., 12(1), 21–32.
[13]. Mahmood, T., Ullah, A. (2022). Drone detection using YOLOv4 and drone-vs-bird classification. Proc. Int. Conf. on Automation and Computing (ICAC).
[14]. Ganti, R., Pham, H. (2020). Deep learning-based UAV detection for security. J. Intell. Robot. Syst., 97(3–4), 515–530.