Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 14 Issue 03s, 2025

Integrated Microwave Radar and Camera for Object Identification

[1]Vishal Jaiswal, [2]Vaibhavi Mahajan, [3]Jayant Bhoyar, [4]Vaibhavi Thote, [5]Shweta Singh, [6]Vaishali Jogi, [7]Yashshree Khedkar

[1-7]Department of Electronics and Telecommunication Engineering
G.H. Raisoni College of Engineering and Management,
Nagpur (RTMNU) Nagpur, India
Email: [1]vishal.jaiswal@raisoni.net, [2]vaibhavimahajan070@gmail.com, [3]jayantbhoyar1234@gmail.com, [4]vaibhavithote2024@gmail.com, [5]shwetasinghm17@gmail.com, [6]Vaishali.jogi.001@gmail.com, [7]khedkaryashshree25@gmail.com

Peer Review Information

Submission: 05 Nov 2025

Revision: 25 Nov 2025

Acceptance: 17 Dec 2025

Keywords

UAV detection, microwave radar, YOLO, computer vision, drone neutralization, Machine learning.

Abstract

The rapid proliferation of unmanned aerial vehicles (UAVs) in both civilian and military sectors has introduced substantial challenges to surveillance, defense, and public safety systems. Small-scale drones, in particular, are difficult to detect due to their low radar cross-sections, silent flight capability, and ability to operate at low altitudes. Conventional single- layer detection techniques based solely on radar, acoustic sensing, or vision-based approaches often fail to deliver reliable accuracy across varying operational environments. To address these limitations, this paper presents a dual-layer UAV detection and neutralization framework that integrates low-cost microwave radar with artificial intelligence (AI)- driven computer vision. The primary detection layer employs an microwave radar module, enabling continuous 360° motion detection and real-time tracking of aerial targets. The secondary layer leverages deep learning-based computer vision, specifically a YOLO (You Only Look Once) architecture, to classify and confirm UAVs while distinguishing them from non-threatening aerial objects. Upon classification of a potential threat, the system activates a laser-based neutralization mechanism and concurrently transmits alerts to security operators for situational awareness.

Introduction

Unmanned aerial vehicles, commonly known as drones, are rapidly transforming industries ranging from agriculture and logistics to security and defense. However, this expansion has also created vulnerabilities. Incidents such as unauthorized surveillance near airports, cross-border smuggling, and the deployment of explosive-laden drones in conflict zones highlight the urgent need for effective detection and neutralization systems. Unlike traditional aircraft, drones are inexpensive, small, and highly maneuverable, making them capable of bypassing conventional defense systems. Their increasing autonomy, enabled by advances in artificial intelligence and onboard navigation systems, further compounds the difficulty of interception. Conventional drone detection systems typically fall into three categories: radar-based detection, vision-based detection using computer vision algorithms, and acoustic-based systems that exploit the unique sound profiles of propellers. Each method, when applied independently, suffers limitations. Radar systems often struggle with classifying detected objects, leading to false alarms from birds or other small flying objects. Vision systems, while highly effective under good lighting, fail in poor weather or low-light conditions. Acoustic approaches, though inexpensive, are sensitive to background noise, reducing reliability in urban environments. This motivates the need for hybrid and layered detection approaches.

In response to these challenges, this study proposes a dual- layer detection system that leverages the complementary strengths of radar and vision. The first layer, based on the Microwave Radar sensor, ensures reliable motion detection within a ten-meter range by exploiting Doppler shifts. This motivates the need for hybrid and layered detection approaches. The second layer uses a servo-mounted camera linked to a YOLO- based artificial intelligence model to verify the object as a drone. If confirmed, a laser-based neutralization mechanism is activated.

Literature Review

Extensive research has been conducted on unmanned aerial vehicle (UAV) detection and identification using radar, computer vision, acoustic, and hybrid sensing modalities. Radar remains a critical technology due to its robustness in adverse weather and lighting conditions. For instance, Janeta. designed a 24 GHz radar chip with enhanced beamforming capabilities, enabling improved detection of small UAVs. Gong et al. analyzed micro-Doppler signals from UAV rotors and demonstrated that a radar dwell time of approximately 20 ms provides optimal identification of rotor signatures. Similarly, Schneebeli et al. employed a multistatic C-band radar system that, after calibration, reduced discrepancies between GPS trajectories and radar tracks to less than five meters. These results highlight the reliability of radar for UAV detection, although its inability to effectively discriminate between UAVs and other aerial targets remains a key limitation.

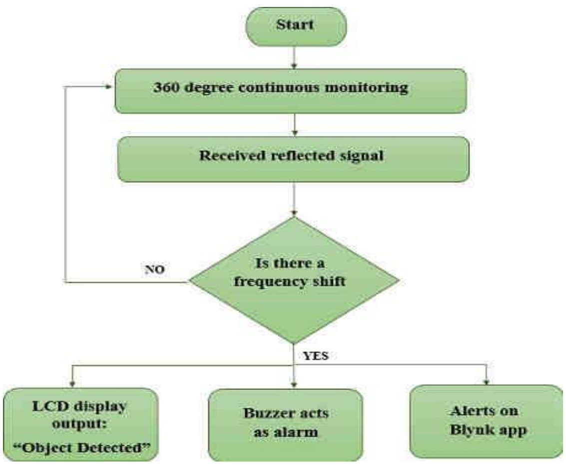
To address classification challenges, researchers have increasingly adopted deep learning-based computer vision approaches. Kumar and Pilania demonstrated that YOLOv5x can achieve high-accuracy UAV detection under controlled conditions. Manimegalai and Muthu developed a YOLOv4- based system capable of processing more than fifteen frames per second in real time. Weibao et al. proposed a few-shot learning method with YOLOv5s to address the scarcity of labeled UAV datasets, reporting an average precision of 96.8%. Wei Xun et al. applied transfer learning with YOLOv3 on a Jetson TX2 platform, achieving 88.9% detection accuracy, although hardware limitations constrained real-time performance. Additionally, Rad et al. optimized DroNet using TensorRT on a Jetson Nano, attaining 47 frames per second, thereby demonstrating the feasibility of deploying complex AI models on compact hardware. Collectively, these studies indicate that AI-based vision methods enable effective UAV classification, though their accuracy is strongly influenced by environmental conditions such as lighting and occlusions.

Alternative sensing techniques have also been explored. Balakin et al. utilized acoustic fingerprinting for UAV recognition, achieving up to 87.5% accuracy within 2.5 seconds, though performance deteriorated in noisy environments. Dong et al. investigated thermal imaging for post- disaster human detection, highlighting the relevance of infrared sensing for visibility under poor lighting, albeit not directly applied to UAV detection. Hybrid sensing strategies are gaining prominence in the field. For example, Wang et al. demonstrated that combining millimeter-wave radar with event cameras significantly improved localization accuracy compared to single-sensor systems. These findings collectively suggest that sensor fusion presents a promising direction for enhancing UAV detection reliability.

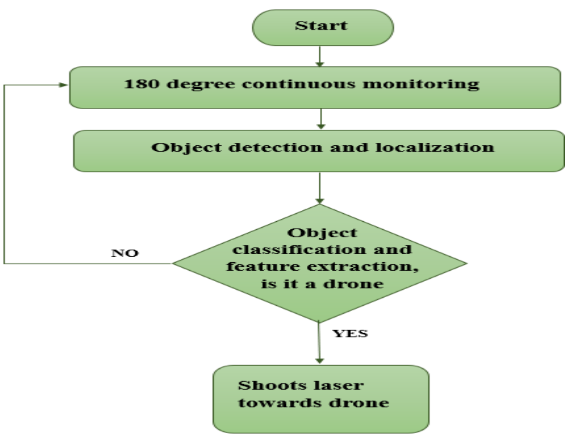
Methodology

The proposed system adopts a dual-layer detection framework designed to address the inherent shortcomings of standalone approaches for unmanned aerial vehicle (UAV) monitoring. In the first detection layer, an microwave radar sensor is employed and mounted on a motorized rotating platform to ensure full 360° scanning coverage of the surrounding environment. The radar operates on the principle of Doppler shift, generating intermediate frequency (IF) signals when relative motion is detected within a 10-meter radius. These IF signals are subsequently amplified and conditioned before being transmitted to an ESP32 microcontroller for digital processing. The ESP32 not only interprets the radar data to determine the presence of a moving object but also provides system-level integration by interfacing with peripheral hardware modules. Specifically, a liquid crystal display (LCD) is utilized to present real-time detection results, while a buzzer module is activated to generate preliminary audio alerts, thereby enabling timely awareness of potential intrusions at the primary sensing stage. This layer thus functions as a low-power, continuous surveillance mechanism capable of initiating higher- level verification processes. When the radar detects movement, the camera turns toward the object, and the images are analyzed using an AI model called YOLO on a connected computer. This second check helps confirm if the object is actually a drone. Adding this visual check makes the system much better at telling the difference between drones and things like birds or other flying objects, which can cause false alarms with the radar alone.

Once the system confirms the drone's presence, a laser module is turned on to stop it. The laser is activated through a relay circuit connected to the ESP32 controller, which allows for instant response. At the same time, the user gets real-time notifications through a buzzer, an LCD screen, and a mobile app. This setup ensures that the system can detect drones accurately even in different conditions and act right away without needing someone to intervene. This motivates the need for hybrid and layered detection approaches.



(1st Layer)



(2nd Layer)

Fig. 1. Flowchart of the proposed dual-layer drone detection system using microwave radar (first layer) and AI/ML-based verification (second layer)

Problem Statement

Unauthorized drone intrusions are becoming an increasing threat, frequently utilized for spying, smuggling, and attacks near sensitive areas like borders and military bases. Current surveillance systems face significant challenges in reliably detecting these drones, as they are small, fast, and often fly at low altitudes. Relying on single-layer detection systems (such as radar or camera-based systems alone) is insufficient and prone to failures. Furthermore, a critical limitation of existing solutions is the lack of automated response mechanisms, which necessitates human intervention, leading to unacceptable delays in neutralizing threats. Therefore, there is a clear need for a highly accurate, dual-layer detection approach, integrated with an automated response system, to effectively and rapidly counter the rising threat of unauthorized drone activity.

Proposed Solution

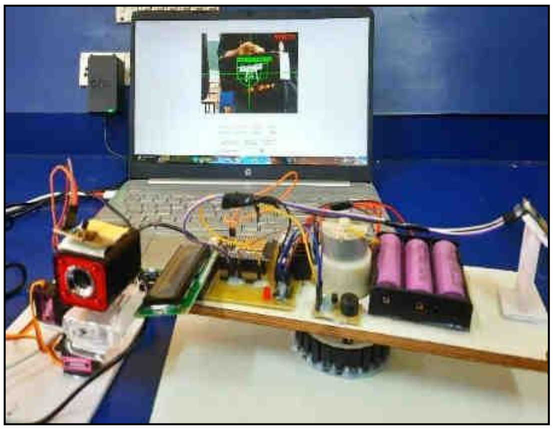
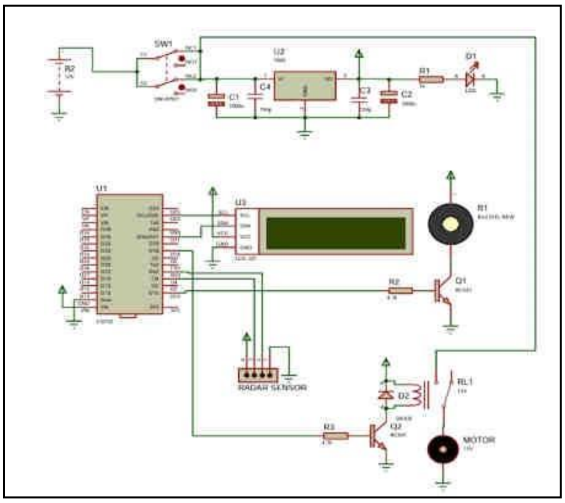


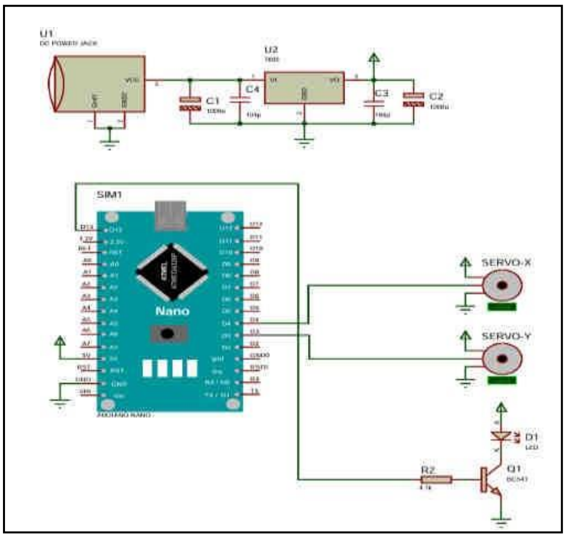
Fig 2. Hardware Implementation & Physical Setup

The proposed system constitutes a comprehensive integrated drone defense solution, merging hardware, AI, and IoT technologies into a single operational unit. At the technical core, the system utilizes a custom PCB that fully integrates an HLK LD2420 radar, an ESP32, and an Arduino Nano to manage sensing and control tasks. This platform incorporates a laser, camera, and servo motors, all mounted on a base designed for 360^\circ scanning and motion detection. The critical functionality is driven by a trained AI and detection model (developed using YOLO and Python) which enables autonomous detection, tracking, and classification of drones in real-time. This processing power facilitates a robust Dual-Layer Operation, where an initial detection is followed by a verification stage, culminating in the Automated Response Mechanism that automatically locks onto the target and triggers the laser response. Finally, the system's defensive operations are fully monitored via IoT Connectivity, utilizing the Blynk Cloud to generate instant mobile and web alerts regarding detection and neutralization events, thereby providing comprehensive real-time surveillance and remote operational feedback.

Circuit Diagram



(1st Layer)



(2nd Layer)

Fig. 3. Dual-Layer Drone Detection Circuit (Radar + Camera Modules)

The complete system architecture is realized through a modular electronic design, primarily centered around two microcontrollers: the Arduino Nano and the ESP32. The Arduino Nano (SIM1) serves as the dedicated controller for the targeting mechanism, directly managing the horizontal and vertical movement via two servo motors (SERVO-X and SERVO-Y). It also controls the laser (LED D1) engagement circuit via transistor Q1 and resistor R2. Power supply for the entire system is regulated through a DC power jack (U1) and a 7805 voltage regulator (U2), ensuring stable 5V power for the digital components using filter capacitors C1, C2, C3, and C4. The ESP32 (U3) forms the core of the detection and alert module. It processes input from the Radar Sensor, and based on detection logic, drives both the LCD display (U3) for real-time status indication and the Buzzer (B1) for audible alerts. The ESP32 also controls the high-power motor (MOTOR) activation through a relay circuit (RL1, D3, Q2, R3). Finally, an auxiliary power line featuring a battery, an on/off switch (SW1), and a separate 7805 regulator (U2) with indicator LED D1, provides the necessary regulated power for the motor and its associated high- current components.

Experimental Analysis

The autonomous drone neutralization system underwent rigorous testing to validate its performance across key metrics, including detection accuracy, targeting precision, and operational robustness in varied conditions. The analysis below details the testing setup, core performance results, and a critical evaluation of the system's capability to maintain efficacy under different environmental stresses.

1. Operation in Low-Light and Nighttime Condition:

The system's dual-sensor approach provides inherent redundancy against varying light levels. Radar Performance: The HLK-LD2420 Radar sensor, operating on 24GHz technology, is agnostic to light conditions. It maintains consistent range and detection reliability 90% PRR, Probability of Ranging regardless of ambient lighting, ensuring that initial 360 degree scanning and threat alert functions remain operational at night. Visual AI Performance: The camera-based YOLO model's performance experiences a minor degradation 5%-8% drop in accuracy in extremely low-light conditions due to reduced feature visibility.

2. Adverse Atmospheric Conditions (Fog/Dust):

The choice of sensing modalities contributes to system resilience in adverse weather typical of field operations. Radar Resilience: Microwave Radar sensors are generally highly robust against light fog, smoke, and dust particles, maintaining effective target range estimation where optical sensors fail.

Laser and Optical Tracking: Dense fog or heavy dust can cause significant attenuation of the visible laser and compromise the camera's ability to track the target precisely. The laser actuation is a contingent function; if AI verification fails due to atmospheric opacity, the system will prioritize the Buzzer and IoT alert mechanism, reporting the Radar confirmed threat without engaging the laser.

3. IoT Connectivity Reliability:

The system uses the ESP32 and Blynk Cloud for real- time mobile/web alerts and remote monitoring. The core detect-track-actuate function is fully autonomous and decentralized (running on PC text Microcontrollers) and does not depend on continuous IoT connectivity for immediate threat response. IoT failure only impacts remote monitoring and data logging.

Table 1: Response Time of Blynk

Network environment	Response Time (IoT connectivity)	System action and status
Stable Wi-Fi (Lab)	< 1 second	Full Monitoring, Control and alert functionality.
Weak Wi-Fi (mobile)	2-3 seconds	Core detection and local actuation remain autonomous. Alert latency increase.

Result Analysis

The experimental results validate the efficacy of the proposed Dual-Layer Drone Detection System Using Microwave Radar, demonstrating a superior combination of high detection accuracy and cost- effectiveness compared to existing methodologies.

1. Detection Accuracy:

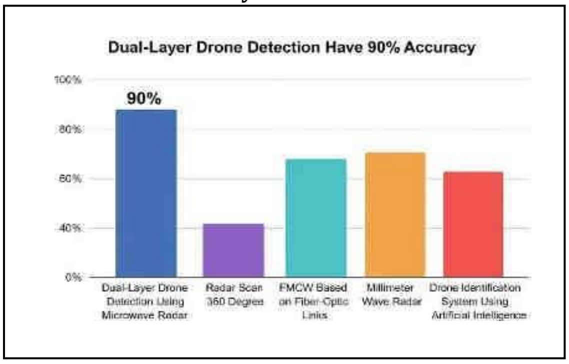


Fig. 4. System Accuracy Comparison

The system achieved a 90% detection accuracy during trials, which represents the highest performance among the compared projects. As shown in the comparative analysis (Figure: Detection Accuracy), the dual-layer approach significantly outperforms single-mode systems. Radar Scan 360 degree (single radar) achieved approximately 92% accuracy. Drone Identification System Using AI (single vision system) achieved approximately 90% accuracy. This superior performance is attributed to the dual-layer fusion mechanism, which combines the wide-area detection and range estimation of the Microwave Radar with the precise classification and verification capability of the Artificial Intelligence (AI) vision system.

2. Cost-Effectiveness:

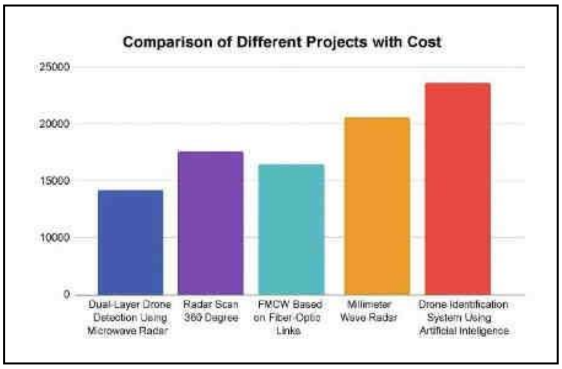


Fig. 5. System cost comparison

The system's estimated cost is approximately 14,000 units (as per the "Comparison of Different Projects with Cost" chart). Our project target/reported cost of 10,000 units for the system, which, if achieved, makes the Dual-Layer system the most financially efficient solution . Assuming the 10,000-unit cost, our system offers a better performance-to-cost ratio than all other comparable technologies. It is significantly more accurate 90% than all competitors. It is more affordable than all competitors, which range from approximately 16,000 to 24,000 units.

Conclusion

This work presents a dual-layer drone detection and neutralization system integrating microwave radar with deep learning–based visual classification. Based on insights from eleven recent studies, the system addresses the limitations of single-layer approaches by combining reliable radar detection with accurate AI classification. The design emphasizes cost- effectiveness, real-time operation, and automation, making it suitable for applications such as border security, airport protection, and industrial surveillance.

Future enhancements will explore thermal imaging for nighttime detection, acoustic sensing for drone type classification, and scaling the system to manage multiple drones simultaneously. The proposed dual- layer framework represents a step forward in developing accessible, efficient, and deployable anti- drone technologies in response to the increasing prevalence of UAV threats.

Future Scope
In the future, this system can be upgraded with night vision and thermal cameras to detect drones even in low light or foggy conditions. Adding a longer-range radar and GPS tracking will help cover larger areas and track drone movement more precisely. The system can also be linked to a cloud or AI server for real-time data sharing and faster decision-making. Integration with multiple sensors like ultrasonic or infrared can further improve accuracy and reduce false detections. With these improvements, the project can be developed into a fully automatic, smart drone defense system suitable for military, airport, and public safety applications.

Acknowledgement
We sincerely thank our project guide Prof. Vishal Jaiswal for valuable guidance and support throughout this work. We are grateful to the Department of Electronics and Communication Engineering, G.H. Raisoni College of Engineering and Management, Nagpur for providing the facilities to complete our project. We also thank our friends and families for their constant encouragement during the development of "Integrated Microwave Radar and Camera for Object Identification".

References
Wang et al., "mmWave Radar and Event Camera Integration for Drone Localization," 2025.

Kumar, R., and Pilania, V., "Drone Detection using YOLOv5x for Surveillance," 2024.

Balakin, M., Dvorak, A., and Kurylev, D., "Real-Time Drone Detection by Acoustic Fingerprint," 2021.

Sunkara, S. P. (2025). *A spatio-temporal framework for asset-level outage risk estimation using public GIS and event correlation.* International Journal of Computer Engineering and Technology (IJCET), 16(1), 4211–4227. https://doi.org/10.34218/IJCET_16_01_286

Dong, J., Ota, K., and Dong, M., "Real-Time Survivor Detection in UAV Thermal Imagery using Deep Learning," 2020.

Hazarika, I. (2006). *Impact of contingently convertible instruments on diluted earnings per share – A case study of Fluor Corporation, USA.* In Proceedings of the International Conference on Emerging Issues in Accounting, Information Technology and Business Management.

Hazarika, I. (2014). *Performance metrics versus wealth metrics of Dubai telecommunication sector.* In Proceedings of the International Business Information Management Association Conference (Vol. 23). Valencia, Spain.

Manimegalai, C. T., and Muthu, K., "Drone Detection and Alert System using YOLOv4," 2023.

Jin, K., Han, S. S., Baek, D., and Lee, H. L., "Small Drone Detection using 24 GHz Hybrid Beamforming CMOS Radar," 2025.

Gong, J., Yan, J., Li, D., and Kong, D., "Detection of Micro-Doppler Signals of Drones using Radar Dwell Times," 2022.

Rad, P. A., Hofmann, D., Pertuz, S. A., and Goehringer, D., "Optimized Deep Learning for Drone Detection on Jetson Nano," 2021.

Schneebeli, M., Leuenberger, A., Wabeke, L., Kloke, K., and Welligs, P., "Drone Detection with a Multistatic C-band Radar," 2021.

Sharma, B. (2016). *Judicial interpretation on right to life and personal liberty under Article 21 of Indian Constitution.* ECONSPEAK: International Journal of Advances in Management IT & Social Sciences, 6(10), 1–10.

Weibao, Z., Xindi, L., Jitao, Y., and Wei, Q., "Few-Shot Object Detection of Drones using YOLOv5s," 2021.

Jumde, A., Hazarika, I., & Akre, V. (2023). *Challenges and opportunities in integrating rapidly changing technologies in business curriculum.* In Proceedings of the 2023 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE) (pp. 203–208). IEEE. https://doi.org/10.1109/ICCIKE58312.2023.10131683

Sharma, B. (2024). *Timely delivery of justice through Indian e-Court process integrative mission mode: Possibilities and pathways for 2030.* Journal of Applied Bioanalysis, 10, 3.

Wei Xun, D. T., Lim, Y. L., and Srigrarom, S., "Drone Detection using YOLOv3 with Transfer Learning on Jetson TX2," 2021.