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Review of AI-augmented multisensor architectures for detecting and neutralizing UAV threats

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Abstract

The unconventional proliferation of unmanned aerial vehicles (UAVs) has led to an urgent demand for advanced counter-unmanned aerial system (C-UAS) technologies capable of accurately detecting, classifying, and mitigating these threats. This paper offers a comprehensive overview of current detection methodologies, including radio frequency (RF) signal analysis, deep learning-based visual recognition (e.g., YOLOv5), thermal imaging, acoustic pattern classification using convolutional neural networks (CNNs), and integrated sensor systems utilizing attention mechanisms. A comparative analysis is conducted based on key performance indicators such as precision rates, mean average precision (mAP), operational range, response time, and robustness to environmental noise. These performance metrics are organized into a summarizing table for clarity. Additionally, several real-world C-UAS platforms such as DedroneTracker, AUDS, and Fortem DroneHunter are examined to illustrate approaches to full system integration. The discussion also encompasses the legal and ethical considerations, the implications of autonomous UAV swarms, and emerging trends in C-UAS strategies, especially those leveraging edge computing and cognitive modeling. The findings support the effectiveness of adaptable, modular, and interpretable counter-drone frameworks suited for dynamic and high-threat environments.

Keywords: AI-based drone detection, Autonomous UAV surveillance, CNN-LSTM architectures, Cybersecurity of UAVs, Deep learning, computer vision, Geolocation technologies, GPS spoofing detection, Machine learning, Object detection (YOLO, SSD, Faster R-CNN), Radar-based detection, Acoustic sensing, Infrared and thermal imaging, Sensor fusion, SLAM, Geofencing, UAV classification, Drone threats, UAV detection, Drone identification, UAV incidents, Radio frequency (RF) detection, UAV traffic management (UTM), Unmanned aerial vehicles (UAVs), Visual tracking, LiDAR.

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1. Introduction

In recent years, unmanned aerial vehicles (UAVs) have experienced rapid growth due to their affordability, portability, and versatility. Their widespread adoption spans various civilian sectors, including agriculture, logistics, environmental monitoring, and public safety. However, alongside their benefits, the increasing deployment of UAVs has also led to a surge in security incidents involving unauthorized or malicious use. Reports from organizations such as Dedrone suggest a steady annual increase in UAV-related threats to critical infrastructure, with actual occurrences potentially being several times higher than what is officially documented [1, 2]. These threats range from violations of privacy and acts of cyber surveillance to disruptions at airports and terrorist activities.

To counter these emerging challenges, current counter-UAS (C-UAS) solutions incorporate a range of detection, identification, and neutralization methods. These include radio frequency (RF) signal analysis, acoustic sensing, visual and infrared imaging, radar-based systems, or integrated multisensor frameworks [3-6]. The use of artificial intelligence (AI), particularly through convolutional neural networks (CNNs), deep learning-based tracking, and real-time object recognition models, has significantly improved the reliability and adaptability of these systems–even in complex environmental conditions or high-noise areas.

Despite technological advancements, there remains a lack of comprehensive and unified research in this domain. Many studies tend to focus narrowly on individual detection techniques or are limited to specific components of a full C-UAS system. Moreover, few investigations thoroughly assess aspects such as cybersecurity resilience (e.g., GPS spoofing, adversarial AI attacks), detection speed, scalability, and the trade-offs between computational efficiency and detection accuracy [7-9].

This paper presents a systematic review of C-UAS technologies, with an emphasis on multisensor integration and AI-driven methods. Over 60 publications from 2018 to 2024 were analyzed, primarily sourced from Scopus, IEEE Xplore, and MDPI databases, based on keywords such as "C-UAS", "drone detection", "sensor fusion", "anti-drone", and "deep learning". Selection criteria included scientific contribution, technical novelty, and relevance to real-world deployment scenarios.

The main contributions of this review include:

- A structured analysis of detection, classification, and neutralization techniques;
- A comparison of sensor modalities and AI architectures based on performance metrics such as detection accuracy, response time, and noise robustness;
- A summary of real-world system architectures and implementation case studies;
- An outline of current challenges and future research directions in the development of scalable and reliable C-UAS systems.

2. Background

In the context of increasing UAV proliferation, significant research efforts have been devoted to the development of advanced detection, classification, and mitigation techniques. This section systematically reviews the principal modalities employed in counter-UAS (C-UAS) systems, including radio frequency (RF)-based detection, computer vision methods using RGB and infrared imagery, acoustic sensing, and radar technologies. Each approach is evaluated in terms of operational reliability, environmental adaptability, and algorithmic performance. Furthermore, attention is given to emerging trends in sensor fusion and AI-driven signal interpretation, which offer enhanced detection capabilities in complex environments. The section concludes with an overview of contemporary countermeasure techniques, ranging from passive interference methods to active neutralization systems.

3. Materials and Methods

Radio frequency (RF)-based tracking is one of the most widely adopted approaches for identifying unmanned aerial vehicles (UAVs), largely because it enables monitoring and disruption of communication channels such as control links, telemetry, and payload transmissions. These signals often operate within the 2.4 GHz and 5.8 GHz ISM bands and can be captured using passive RF receivers, eliminating the need for a direct line of sight. This makes RF detection particularly valuable in environments with limited visibility or urban obstructions [10-13].

In modern counter-UAS frameworks, there has been a growing emphasis on leveraging software-defined radio (SDR) platforms [14, 15]. These systems provide a flexible, programmable infrastructure for real-time signal processing and allow on-the-fly updates to detection algorithms, thereby supporting multiple UAV communication standards. SDRs typically support modular operations, including spectrum scanning, segmentation over time windows, and adaptive channel filtering [16-19]. This flexibility enables seamless integration with AI-powered classification modules.

Machine learning (ML) techniques have demonstrated significant potential in distinguishing UAV-generated RF signals from background interference. Approaches such as support vector machines (SVMs), decision tree classifiers, and long short-term memory (LSTM) networks have been employed to enhance signal categorization under noisy conditions. Notably, blind classification techniques, which do not rely on prior knowledge of communication protocols, allow detection even when transmissions are encrypted or deliberately obfuscated [20].

Despite their advantages, RF-based systems face challenges when dealing with autonomous drones that do not rely on active communication links. Additionally, such systems are vulnerable to signal degradation caused by multipath propagation and ambient noise. However, RF analytics can provide critical insights when used in conjunction with other sensors as part of a broader multi-modal detection framework.

Figure 1 outlines the key stages in an SDR-based UAV detection pipeline, including signal capture, pre-processing, feature extraction, and machine learning-driven classification [21-23]. Table 1 presents a comparative analysis of SDR systems with respect to detection range, classification accuracy, and robustness to noise.

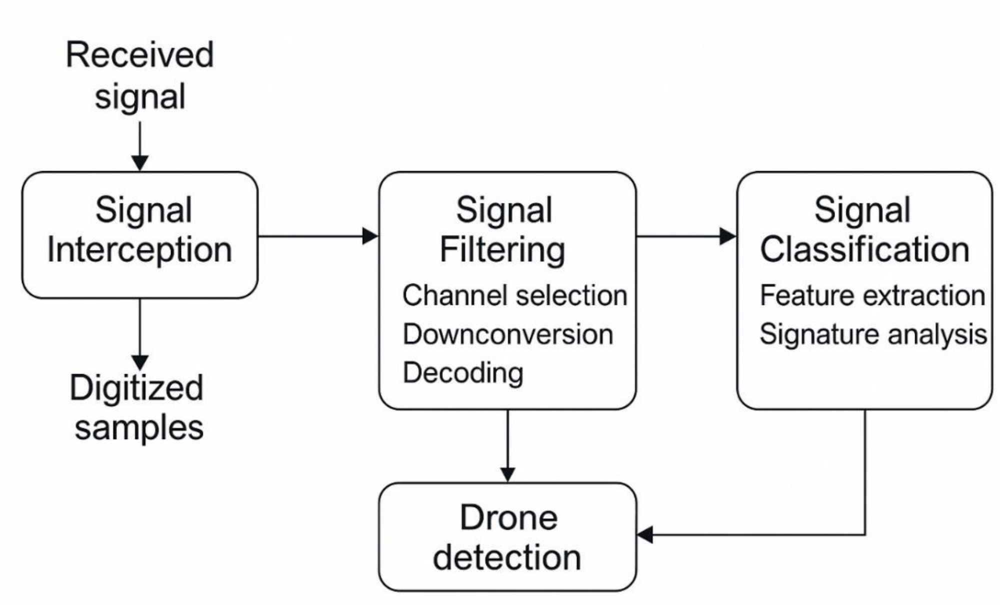

Figure 1.
Architecture of an SDR-based drone detection system, highlighting signal capture, filtering, and classification blocks.

Table 1.
Comparison of SDR platforms for UAV signal detection.

SDR Platform	Frequency Range (MHz)	Classification Accuracy (%)	Detection Range (m)	Noise Robustness
HackRF One	1–6000	78	200	Medium
USRP B200	70–6000	91	350	High
RTL-SDR	24–1766	65	100	Low
BladeRF xA9	47–6000	88	300	Medium

A comprehensive counter-unmanned aerial system (C-UAS) typically comprises a three-layered architecture, encompassing sensing and data acquisition, analytical processing and classification, and response execution.

The first layer is responsible for environmental monitoring and includes a distributed network of sensors such as radio frequency (RF) detectors, radar units, infrared (IR) and LiDAR sensors, and acoustic arrays. These devices operate continuously to scan airspace and collect either raw data or pre-processed features, which are then forwarded to a centralized processing hub.

At the second level, signal processing and target identification are carried out using advanced artificial intelligence (AI) methods. Techniques such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, transformer-based models, and composite deep learning architectures are applied [24, 25]. A dedicated data fusion module integrates sensor outputs using approaches such as early-stage fusion, decision-level fusion, or attention-driven models to improve detection accuracy and situational awareness.

Finally, the response and mitigation layer interprets the processed data by comparing it to predefined boundaries such as regulatory geofences or no-fly zones. Based on this evaluation, the system activates countermeasures–ranging from signal jamming and control takeover to physical interception or alerting relevant personnel–depending on the defined engagement protocol [26-29].

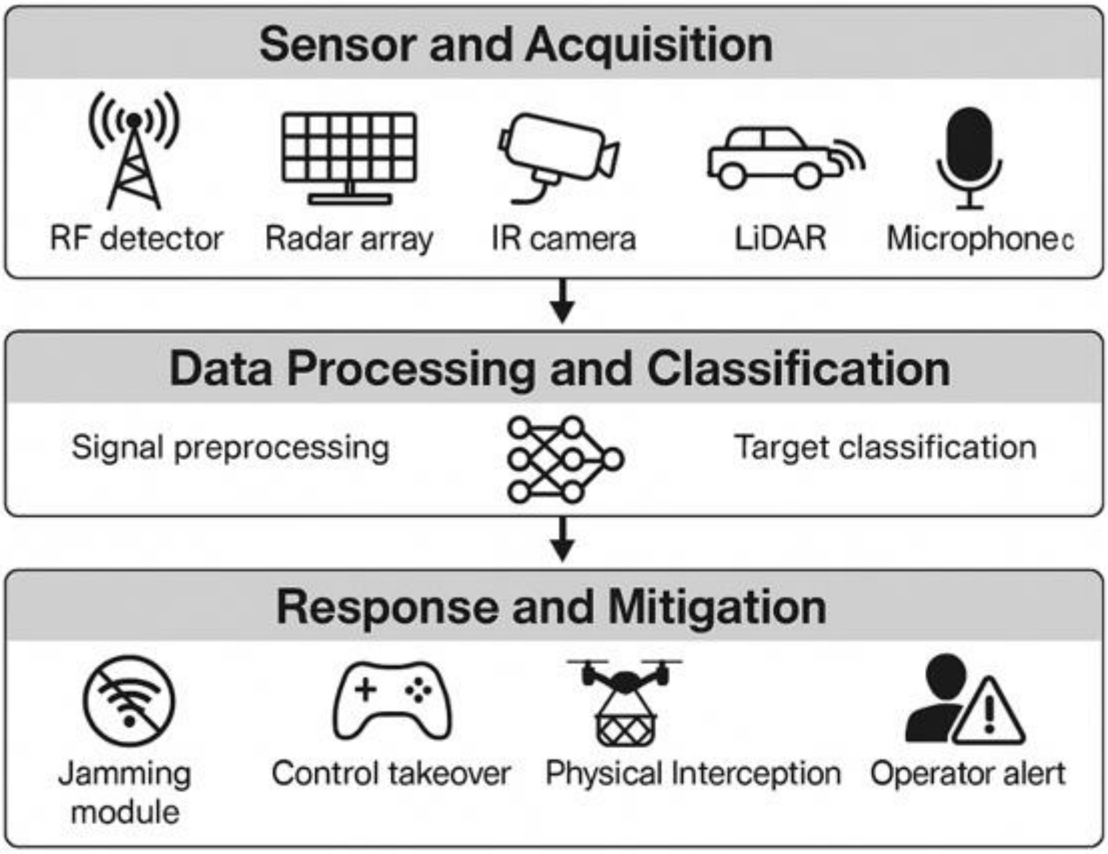

Figure 2.
General architecture of a counter-UAS (C-UAS) system.

Figure 2 presents the generalized architecture of a multisensor C-UAS system, showing the layered integration of sensing, analytics, and neutralization components.

Visual-based detection has emerged as one of the most dynamic and actively developed methods within modern counter-UAS (C-UAS) systems. This approach relies on analyzing imagery from RGB cameras and thermal infrared (IR) sensors to detect and track UAVs based on distinct characteristics such as shape, movement, and visual cues [18]. These techniques are particularly effective in urban environments and daylight conditions, where drones can be more easily distinguished from background elements using computer vision algorithms.

Prominent convolutional neural network (CNN) models msuch as YOLO (You Only Look Once), SSD (Single Shot Multibox Detector), and Faster R-CNN are widely employed due to their high detection speed and strong object recognition performance [30-32]. Notably, versions such as YOLOv4 and YOLOv5 have demonstrated effective results in both visible and thermal spectra, even in visually complex scenarios involving multiple moving entities and cluttered backgrounds.

Thermal imaging plays a crucial role in low-light or nighttime surveillance. UAVs generate heat signatures through their electronic components and motors, which can be captured by IR sensors, enabling detection even in the absence of visible indicators [33]. Combining RGB and IR data through multimodal fusion techniques has further improved detection accuracy under varying lighting and weather conditions [34-37].

Transfer learning has proven valuable in this domain, particularly when training data is limited. By fine-tuning pre-trained visual models, C-UAS systems can adapt to drone-specific datasets, including synthetic or augmented imagery enhancing robustness to visual noise and domain variability.

Performance of these detection models is typically evaluated using metrics such as mean average precision (mAP@0.5), true positive rate (TPR), false positive rate (FPR), and inference speed measured in frames per second (FPS). Comparative studies indicate that YOLOv5 offers a strong balance between detection accuracy and processing speed, outperforming SSD-based alternatives in urban environments characterized by high noise levels and visual complexity [38-41].

Although visual detection systems offer strong performance in many environments, they face significant limitations under certain conditions. Challenges such as visual occlusion, adverse weather (e.g., rain or fog), low video resolution, and restricted fields of view can degrade their effectiveness. To address these shortcomings, modern multisensor frameworks often integrate visual inputs with complementary modalities such as radio frequency (RF) analysis, radar, or LiDAR. This fusion enhances detection robustness across a wider range of operational scenarios.

Figure 3.
Sample UAV detection in urban scenes using YOLOv5 (with RGB and IR fusion).

Table 2.
Comparison of visual detection models for UAV recognition tasks.

Model	Accuracy (mAP@0.5)	Speed (FPS)	Noise Robustness
YOLOv3	85.4%	45	Medium
YOLOv5s	88.7%	70	High
YOLOv7-tiny	89.1%	80	High
EfficientDet-D0	82.3%	35	Medium
ResNet50 + FPN	86.2%	28	Medium

Acoustic detection methods identify unmanned aerial vehicles (UAVs) by capturing distinct sound signatures produced by their propulsion systems. These sounds typically originate from propeller blade motion, motor vibrations, and air turbulence, and they generally fall within the audible frequency range of 20 Hz to 20 kHz. Despite environmental noise from wind, traffic, or animals, UAV audio patterns often exhibit recognizable low-frequency harmonics and modulations that can be isolated with signal processing techniques [42-45].

One of the main advantages of acoustic detection is its passive nature, enabling UAV identification without the need for direct visual contact. Contemporary systems use microphone arrays along with sophisticated audio processing algorithms [46]. These may include spectral decomposition, extraction of Mel-frequency cepstral coefficients (MFCCs), and time-delay-of-arrival (TDOA) analysis to localize sound sources. These audio features are frequently used in conjunction with machine learning classifiers such as support vector machines (SVM), k-nearest neighbors (KNN), and convolutional neural networks (CNNs).

Deep learning architectures—particularly CNNs, recurrent neural networks (RNNs), and long short-term memory (LSTM) models—are widely applied for drone audio classification [47-49]. Trained using MFCCs and spectrogram data, these models have achieved classification accuracy rates exceeding 90% in complex, noise-rich environments. Attention-based mechanisms further improve performance by focusing on the most informative portions of the audio spectrum.

Some systems process raw waveform data and spectrograms concurrently to capture both temporal and frequency-domain information. Others use frequency masking or adaptive filtering to prioritize frequency bands specific to UAV activity [50, 51]. These techniques support the detection of various UAV types, including both multirotor and fixed-wing models, even in the presence of competing airborne noise sources.

To estimate the drone's location, TDOA-based triangulation across spatially separated microphones is often employed, enabling both direction and range estimation. When integrated into hybrid systems that combine acoustic and RF-based sensing, these approaches provide greater resilience against occlusion and electromagnetic interference, thereby enhancing overall detection reliability [52-54].

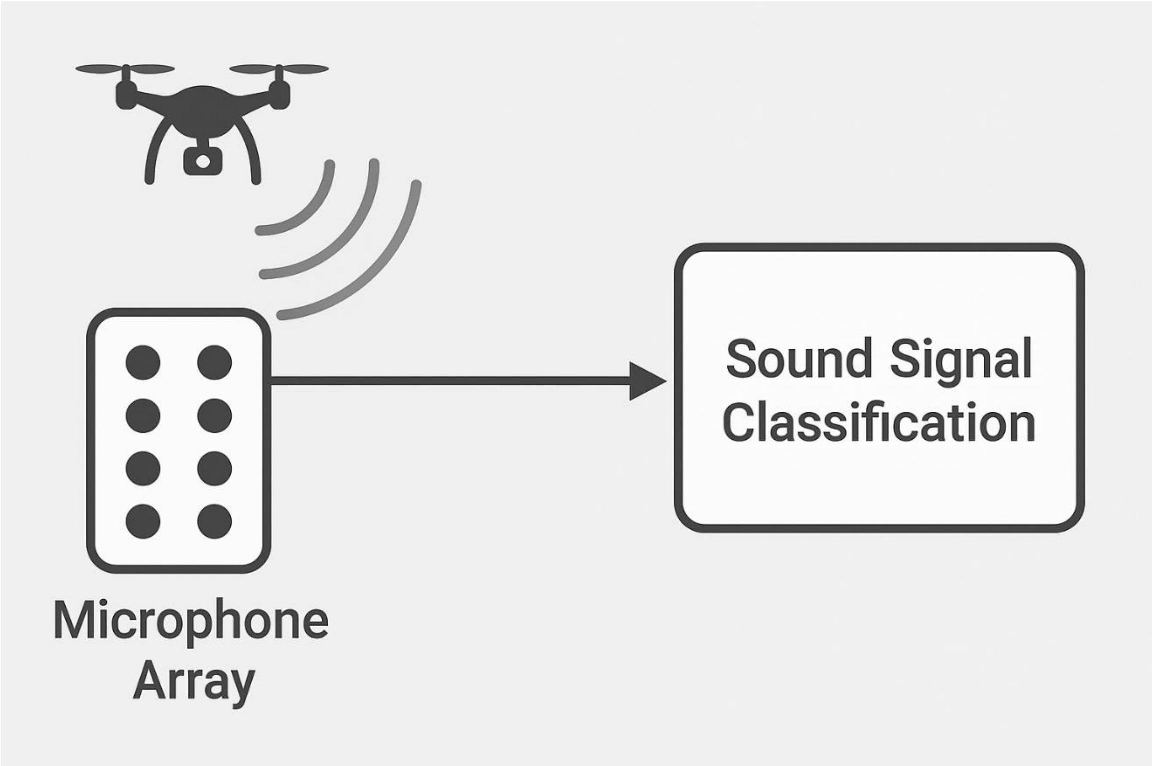

Figure 4.
Schematic of an acoustic UAV detection system featuring a microphone array and neural-network-based audio classification.

Table 3.
Performance of neural-network-based acoustic classification for different UAV models.

UAV Model	Classification Algorithm	Accuracy (%)	Range (m)	Noise Robustness
DJI Phantom 4	CNN (spectrogram-based)	91.5	120	High
Parrot Anafi	SVM with MFCC features	85.2	90	Medium
DJI Mavic Air	LSTM with spectral inputs	88.7	110	High
Hubsan X4	Decision Tree (manual features)	76.3	60	Low

Table 4.
Sensor fusion configurations and their detection characteristics.

Sensor Configuration	Accuracy (%)	Response Time (ms)	Advantages	Limitations
Camera + Radar	92.3	180	Accurate while moving	Synchronization complexity
SDR + RGB/IR Camera	94.6	150	Effective in noisy environments	High computational cost
Microphones + Camera	86.8	140	Passive detection	Weather-dependent performance
SDR + Radar + Camera	96.5	210	Maximum reliability	Expensive and complex setup

Radar-based detection systems are widely used in UAV monitoring due to their ability to operate effectively in challenging environmental conditions, including poor weather, low visibility, and over extended distances. Although small

UAVs tend to exhibit low radar cross-sections (RCS), often under 0.01 m^2, advancements in radar technologies such as frequency-modulated continuous wave (FMCW) and coherent Doppler systems enable the detection and tracking of these targets [55-57]. These systems can also estimate an object's speed and flight path, which aids in distinguishing drones from non-threatening objects like birds.

Modern developments in radar technology place particular emphasis on multiple-input multiple-output (MIMO) radar configurations. These architectures enhance spatial resolution and reduce susceptibility to signal reflections caused by complex terrain or urban structures [58]. When paired with deep learning algorithms, specifically convolutional or recurrent neural networks applied to range-Doppler data, radar systems have achieved high classification accuracy—even in environments with significant noise and clutter.

To improve overall detection reliability, radar outputs are frequently integrated with data from other sensor types, including infrared (IR), radio frequency (RF), and optical sources [59-61]. Such multisensor systems leverage the strengths of each modality; for example, IR imaging performs well at night, RF signals can penetrate barriers, and acoustic signals can detect UAVs that are visually obscured. Fusion approaches may occur at the raw signal level (early fusion) or at the decision level, often supported by models such as LSTMs or attention-based networks to enhance temporal and spatial awareness [62-64].

Comprehensive multisensor systems can ingest data from diverse input sources ranging from RF receivers and thermal cameras to acoustic arrays and radar modules–providing a more resilient and accurate detection framework [65]. Deep learning architectures developed for these systems often include specialized processing branches: convolutional neural networks for handling image and video input, recurrent or attention-based models for sequential data, and spectral analysis techniques to interpret RF signals. This heterogeneous integration significantly improves detection robustness, especially in scenarios involving occlusion, signal jamming, or spoofing attempts [66, 67].

Multisensor fusion strategies are generally categorized into two primary types: early fusion and late fusion. In the early fusion paradigm, raw data or low-level features from multiple sensors are integrated prior to model training. This unified input is then processed collectively, allowing the model to learn cross-modal correlations from the start [68]. In contrast, late fusion involves training independent models for each sensing modality. The outputs from these models are later aggregated using mechanisms such as ensemble learning, meta-classifiers, or attention-based integration methods to arrive at a final decision [69-72].

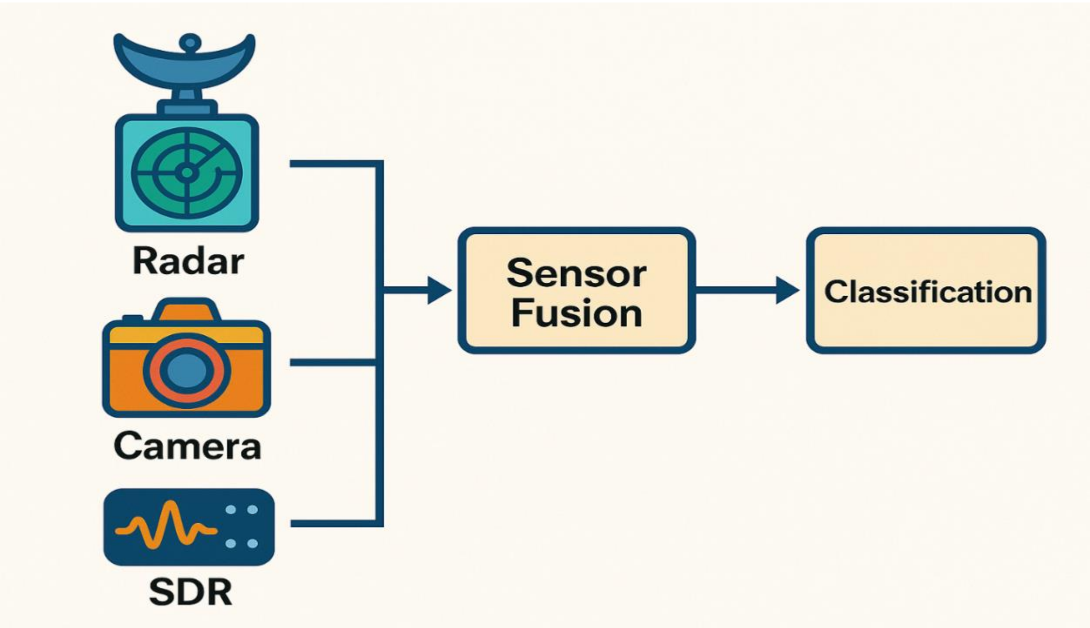

Figure 5.
Fusion strategies in multisensor C-UAS architectures.

Table 5.
Comparative performance of multisensor configurations.

Sensor Configuration	Accuracy (%)	Response Time (ms)	Advantages	Disadvantages
Camera + Radar	92.3	180	Accurate motion tracking	Complex synchronization
SDR + RGB/IR Camera	94.6	150	Resilient in noisy environments	High computational demands
Microphones + Camera	86.8	140	Passive detection	Weather sensitivity
SDR + Radar + Camera	96.5	210	Maximum reliability	High cost and complexity

Multisensor systems typically include dedicated signal processing modules that handle tasks such as denoising, signal transformation, and feature extraction. Radar and RF inputs are often subjected to spectral domain transformations, while audio data is commonly processed using Mel-frequency cepstral coefficients (MFCCs) alongside convolutional recurrent neural networks (CRNNs). Visual data is processed through object detection models like YOLO or through semantic segmentation frameworks. The extracted features from these modalities are then passed to a multi-class classification engine, which contributes to constructing a dynamic threat map that feeds into the system's real-time response mechanism [73-75].

The countermeasure component of a C-UAS system varies depending on the operational context. In civilian settings, non-destructive techniques such as RF jamming and GNSS spoofing are prevalent. In contrast, military applications may involve more aggressive responses, including high-powered jammers, laser-based systems, or drone-based interceptors. Alternative mitigation strategies include cyber takeovers, containment nets, or command-triggered self-neutralization [76, 77]. However, these approaches often face limitations related to regulatory compliance and operational safety.

Finally, Table 5 presents performance metrics derived from a selection of multisensor fusion studies reviewed in the literature, highlighting detection accuracy, response latency, and sensor-specific reliability.

Table 6.
Performance comparison of fusion strategies in literature.

Reference	Fusion Type	Modalities Used	Accuracy (%)	Notable Advantage
Mazhar et al. [32]	Hybrid Fusion	YOLOv5 + IR + GNSS	98.2	Works well in low-light environments
Mo et al. [48]	Late Fusion	LiDAR + RGB	95.7	High precision in complex structures
Tejera-Berengue et al. [51]	Early Fusion	Acoustics + Camera + GPS	93.5	Triangulation of moving targets
Gu et al. [78]	Transformer-based	Visual + IR + LiDAR + GPS	96.8	Attention-based dynamic prioritization

Recent advancements in data fusion methodologies within counter-UAS (C-UAS) systems have led to improved adaptability, robustness, and generalization across operational scenarios. These enhancements are particularly critical in complex environments where drones may be partially obscured, operating under deceptive signals, or concealed across multiple sensing modalities. Looking ahead, the integration of advanced AI frameworks such as transformer-based models and neural ensemble architectures shows promise in addressing more sophisticated threats, including multi-vector attacks and coordinated UAV swarms [79, 80].

Modern counter-UAS (C-UAS) systems are increasingly equipped with active mitigation modules designed to neutralize unauthorized or hostile unmanned aerial vehicles (UAVs) before they can breach restricted airspace [81-83]. These subsystems aim to interfere with or disable drone operations using a range of techniques such as radio frequency (RF) jamming, control signal hijacking, and protections against GPS spoofing. Their implementation varies depending on the application–civilian, military, or critical infrastructure.

Disrupting the communication and navigation channels of UAVs through RF jamming remains one of the most commonly employed methods. Specialized jamming devices emit interference across frequencies commonly used by UAVs, including ISM bands (e.g., 2.4 GHz, 5.8 GHz), GPS frequencies (L1/L2), and data links such as Wi-Fi, 4G, or 5G. Jammers may be omnidirectional, dispersing energy uniformly or directional, which allows focused interference through beamforming [84, 85]. The effectiveness of such systems depends on factors like transmission power, distance to the UAV, and the precision of the interference beam. However, RF jamming carries the risk of unintentional disruption to nearby civilian systems, and its use is tightly regulated in non-military environments [86-88].

In contrast to overt RF interference, more covert approaches involve compromising the drone's control systems through cyber means. By exploiting weaknesses in communication protocols such as MAVLink or unsecured APIs, C-UAS platforms can assume control of a drone’s flight path [63, 89-91]. Common techniques include ground station spoofing, man-in-the-middle (MitM) attacks, and firmware-level infiltration using malware. Additionally, targeted denial-of-service (DoS) attacks on telemetry or GPS synchronization modules can force the UAV into disorientation or trigger an emergency landing. While these tactics can be highly effective, they fall under the broader domain of cyber operations and are subject to strict legal and ethical oversight, especially in peacetime or civilian scenarios [62, 92].

GPS spoofing is an increasingly prominent threat in UAV operations. In such attacks, adversaries transmit counterfeit GNSS signals that deceive UAVs into miscalculating their true position. Consequences can include unintended route deviations, loss of navigational control, or incorrect landing in unauthorized zones. To mitigate these risks, current defensive strategies include the integration of GNSS with inertial navigation systems (INS), directional signal analysis using multiple antenna arrays, and direction-of-arrival (DOA) estimation. In addition, alternative geolocation methods such as Simultaneous Localization and Mapping (SLAM) and Real-Time Kinematic (RTK) positioning are being implemented to bolster positioning reliability and resist spoofing attempts [93-96]. Emerging research is also exploring the potential of quantum-resistant navigation and multimodal geolocation fusion for enhanced spoofing resilience.

To maintain positional accuracy when satellite signals are jammed or falsified, modern C-UAS platforms are increasingly leveraging SLAM-based solutions [97, 98]. These systems–ranging from LiDAR-based SLAM to visual

SLAM (vSLAM) and IMU-integrated SLAM enable drones or tracking agents to generate real-time maps of their surroundings and determine their relative location within those environments [69, 73, 99, 100]. These methods are particularly valuable in urban canyons or indoor areas where satellite visibility is poor or entirely blocked. When used alongside RTK corrections and visual odometry, SLAM enhances positioning robustness and mitigates vulnerability to GNSS spoofing or signal loss. Recent studies have highlighted the importance of SLAM-based navigation not only for autonomous flight but also for accurately pursuing and intercepting potentially hostile UAVs in complex terrain [101-103].

This subsection highlights several leading counter-UAS (C-UAS) platforms that illustrate distinct strategies in system architecture and sensor integration. For instance, DedroneTracker utilizes a multisensor fusion framework that combines visual, radar, and radio frequency (RF) inputs. These data streams are processed via a centralized, cloud-based analytics engine that enables real-time classification of aerial threats and coordinated response actions [104-107].

In contrast, the Anti-UAV Defence System (AUDS) is specifically designed for military deployment. It integrates radar surveillance, electro-optical imaging, and targeted jamming technologies. Operating across both infrared (IR) and radio frequency (RF) bands, AUDS is optimized for detecting and neutralizing threats in complex combat scenarios [108, 109].

The Black Sage platform demonstrates a modular and extensible design, supporting the integration of third-party sensors and countermeasure components depending on mission-specific requirements. This allows for high operational flexibility across diverse environments.

Meanwhile, Fortem's DroneHunter represents a more kinetic response approach. It deploys autonomous drones equipped with AI-driven trajectory prediction and real-time swarm coordination, enabling the direct physical interception of hostile UAVs [110, 111].

Taken together, these platforms suggest that an effective C-UAS solution should prioritize architectural flexibility, scalability, and interoperability at the sensor level to remain adaptable across a range of threat landscapes and deployment contexts.

4. Results and Discussion

Recent developments in counter-unmanned aerial systems (C-UAS) have significantly advanced both detection and neutralization capabilities. However, the diversity of threat scenarios and the operational constraints faced in real-world environments highlight the importance of structured performance evaluation and forward-looking architectural considerations.

To ensure consistent and objective assessment of different C-UAS technologies, a standardized set of performance metrics should be applied. These include precision indicators such as mean average precision (mAP), detection range, response latency, true and false positive rates (TPR and FPR), and resilience to noise interference.

A comparative review of published studies and experimental results refer to Table 4 indicates that hybrid multisensor approaches–particularly those integrating attention mechanisms demonstrate superior performance across multiple evaluation criteria. Visual detection models, like YOLOv5, yield high accuracy in optimal conditions but tend to degrade under challenging environmental influences such as poor lighting or occlusion. Meanwhile, RF and acoustic sensing offer broader range capabilities but may suffer from interference in noise-dense urban areas.

The most consistent and adaptable performance is achieved through AI-enhanced multimodal systems that fuse complementary sensor data. Such configurations leverage redundancy and signal diversity to maintain detection reliability even in complex and dynamic threat environments.

True Positive Rate (TPR) reflects a system's effectiveness in accurately identifying UAV intrusions and is crucial for ensuring that no real threats go undetected. Conversely, a high False Positive Rate (FPR) can lead to operational disruptions, particularly in civilian environments where frequent false alarms may result in reduced trust or operational delays. Response time is another critical factor, especially in scenarios involving high-speed drones where rapid counteraction is essential.

To handle diverse environmental conditions, adaptive C-UAS architectures often employ dynamic sensor prioritization. For example, RF sensing may be prioritized during foggy or low-visibility conditions, while visual tracking systems are favored in clear weather. This flexible approach enhances operational robustness and ensures optimal use of sensing modalities.

As UAV technologies evolve toward autonomous navigation and coordinated swarm behaviors, C-UAS systems face increasingly complex threat profiles. These developments demand enhanced prediction capabilities, real-time behavioral analysis, and support for edge-based AI inference [96-98]. There is a growing emphasis on building systems capable of interpreting intent and contextual behavior using onboard sensors and decentralized processing instead of relying solely on cloud-based analytics. This shift requires advances in lightweight, real-time AI models that can function effectively in bandwidth-constrained or latency-sensitive environments.

Deploying active electronic countermeasures such as GPS spoofing or remote command injection raises significant legal and ethical concerns, particularly in civilian airspace. Many jurisdictions prohibit such actions under telecommunications or air safety regulations. Additionally, the use of opaque or black-box AI in autonomous threat mitigation raises accountability questions. While autonomous countermeasures may be permissible in military settings, civilian deployments demand adherence to principles like proportionality, transparency, and meaningful human oversight to ensure public trust and compliance with international norms.

One of the major barriers to broader C-UAS deployment is the lack of unified technical standards. Many existing systems use proprietary protocols, limiting integration with broader security networks. There is a clear need for standardized data formats, interoperable APIs, and validation frameworks that enable seamless cross-vendor integration. Establishing interoperability at the sensor level is especially critical it would allow modular, mission-driven configurations that can be deployed in diverse contexts, from protecting critical infrastructure to urban airspace monitoring. Modular architectures that support plug-and-play sensor integration will be key to achieving scalable and flexible deployment models.

Table 7.
Comparative Performance Metrics of Drone Detection Methods Based on Sensor Modality and Architecture.

Method	Accuracy (mAP, %)	Range (m)	Response Time (ms)	Noise Robustness	Remarks
SDR Analysis	78–85	1000–1500	80–120	Medium	Depends on spectral density
YOLOv5 (RGB)	90–93	200–300	30–60	Low	Sensitive to lighting conditions
YOLOv5 (IR)	88–91	150–250	35–70	Above Average	Effective in nighttime conditions
Acoustic CNN	85–89	100–200	50–100	Medium	Vulnerable to urban noise
Multisensor (Visual + IR + RF)	94–97	400–800	40–70	High	Reliable under adverse conditions
Multisensor + Attention	96–98	500–1000	45–75	Very High	Used in edge-processing architectures

5. Conclusion

Looking ahead, several key research priorities must be addressed to enhance the effectiveness and adaptability of next-generation counter-UAS (C-UAS) systems:

- Developing robust detection algorithms capable of identifying and responding to coordinated UAV swarm behavior, which poses a significant challenge due to its dynamic and decentralized nature.
- Designing self-evolving neural network models that can generalize to unseen drone types without requiring retraining, thereby reducing system downtime and increasing real-time adaptability.
- Building cognitive architectures that incorporate behavioral inference and contextual analysis to support real-time decision-making and situational awareness.
- Integrating slam-based localization and data fusion techniques with explainable AI (XAI) models to improve operator trust, transparency, and accountability in automated response systems.

In conclusion, the advancement of C-UAS technologies must go beyond algorithmic improvements. Progress will depend on holistic, interdisciplinary efforts that encompass not only technical innovation but also ethical governance, standardized frameworks, scalable system design, and a commitment to openness and interoperability. Only through this comprehensive approach can society develop C-UAS systems that are not only operationally effective but also aligned with legal, ethical, and public safety expectations.

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