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Drone detection in airport environments: A literature review

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ABSTRACT

The increasing use of drones in airport airspace presents a serious challenge to safety and efficiency. Incidents involving unmanned aerial vehicles can cause delays, flight cancellations, and collision risks, raising concerns among airport officials, travelers, and other aviation stakeholders. This study aims to systematically analyze the main drone detection techniques used in airports, identifying research gaps, advantages, and limitations of each method while also highlighting future directions to improve airspace security. Kitchenham's systematic review method was used, with searches carried out from 2014 to 2025. After screening titles and abstracts and applying inclusion criteria, 25 publications were thoroughly assessed. The analysis shows that while radar systems provide the longest detection range (> 10 km) and radio frequency methods achieve the highest classification accuracy (~99%), they often come with higher costs. In comparison, camera-based systems can reach high precision (>90%) at speeds up to 170 FPS, and multimodal solutions show the greatest potential for robustness, with positioning errors below 1.5% of the detection range. Although technical and operational challenges still exist, the combined use of various methods and machine learning techniques shows promise for improving the accuracy and reliability of drone detection at airports.

1. Introduction

The issue of drones at airports poses a significant threat to the security and efficiency of air transport operations, with cases having increased worryingly. Uncrewed Aerial Vehicles (UAVs) or drones, when flying near or within the airspace of an airport, can cause runway closures, flight delays, and, in the worst-case scenario, collide with moving aircraft, potentially leading to catastrophic accidents [1,2].

The urgency for effective detection systems is amplified by the global regulatory landscape. Civil aviation authorities, such as the Federal Aviation Administration (FAA), in the United States [3] and the National Civil Aviation Agency (ANAC), in conjunction with the Department of Airspace Control (DECEA), in Brazil [4], have established strict rules designating the airspace around airports as "no-fly zones" for unauthorized drones. These regulations aim to prevent interference and collisions, but their effectiveness relies entirely on the ability to monitor the airspace and identify violations in real-time. The mere existence of laws is insufficient without the technological means to enforce them, making detection systems the essential first line of defense for airport security.

Furthermore, the unauthorized presence of drones in the vicinity of airports diverts significant resources to identifying and mitigating the threat, including the deployment of security teams and technologies for detecting and neutralizing drones. This problem affects the scheduling of flights and airport logistics, imposing stress and concern on passengers and crew [5,6].

Many techniques have been applied to detect airport drones and mitigate these risks. The most common include camera detection, which uses high-end surveillance systems that identify unauthorized flying objects. Radio Frequency (RF) detection tracks the specific frequency signatures of drones and their controllers. Radar detection, a modified traditional method, identifies small flying objects, such as drones. Sound-based detection relies on identifying the unique acoustic characteristics of drones. Multimodal detection combines several techniques to increase effectiveness and accuracy in identifying drones, presenting many benefits and limitations. However, when taken together, they form a more comprehensive and efficient approach to countering the security challenge posed by airport drones.

Each of these techniques faces significant challenges in airport environments. Variable lighting conditions, long distances, and airport visual obstructions hamper camera detection. RF detection can be complicated due to the wide range of frequency signals present, including air traffic control communications and electronic devices of passengers

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Table 1
Distribution of studies across different databases.

Database	Number of studies
ACM	292
Science Direct	172
IEEExplorer	72
Springer	24
Arxiv	9
Cochrane; Elsevier;	0
PubMed Central;	0
Scielo; PubMed;	0
Scopus;	0
Web of Science	0

Table 2
Inclusion and exclusion criteria for study selection.

Inclusion criteria	Exclusion criteria
Studies published between 2014 and 2025.	Studies published before 2014.
Focus specifically on drone detection in airport environments.	Studies focusing on drone detection in non-airport contexts (e.g., urban, rural).
Presents a practical implementation or experimental results of a detection technique.	Theoretical papers, opinion articles, editorials, or abstracts without new data.
Peer-reviewed articles from reputable journals or conferences.	Non-peer-reviewed manuscripts or pre-prints without subsequent publication.
Full text available in English.	Studies not available in English or in full-text format.
Addresses at least one of the following detection methods: acoustic, visual, RF, radar, or multimodal.	Studies on drone neutralization or policy without a technical detection component.

and staff. While effective at greater distances, radars may struggle to differentiate drones from other small aircraft or birds. Acoustic detection faces the challenge of the airport's high noise levels, where the sound of aircraft engines can overpower and obscure the characteristic sound signatures of drones. Lastly, despite offering a more comprehensive solution, multimodal detection requires the effective integration and synchronization of different technologies, which can be complex and costly to implement on a large scale. Therefore, airports represent particularly challenging environments for the efficient detection of drones.

The current systematic review aims to revise and summarize the various techniques for drone detection applied in airport environments. The benefits, limitations, and special challenges of each method are addressed. It will review studies grouped according to the detection technique and compare them with [7]. The primary objective of this study is to identify gaps in the existing literature, provide in-depth insights into current technologies, and suggest potential areas for future research and development. Furthermore, this review aims to enhance airport security and efficiency by providing valuable insights for researchers, airport security professionals, and policymakers who seek to adopt more effective strategies for detecting and mitigating the threat of lawbreaker drones.

2. Methodology

In this analysis, the Kitchenham approach [7] was applied to establish inclusion criteria and examine the studies under discussion. The strategic selection of keywords and search terms, focusing on "Detection", "Drone", and "Airport", were adopted for the accuracy of the analysis. The search was limited to the period from 2014 to 2025. Challenges were encountered due to term restrictions in specific repositories, such as arXiv, which were overcome through targeted searches. This strategy ensured the acquisition of representative literature, capturing the diversity and innovations in the field. The selected articles were evaluated based on criteria such as the study context, its objectives, samples or datasets used, methodological approaches, main results, limitations mentioned by the authors, conclusions, and recommendations for future research.

Fig. 1 illustrates the data extraction process, and Table 1 presents the distribution of results found in different databases.

In the context of the systematic review, as illustrated in Fig. 1, the inclusion and exclusion criteria, detailed in Table 2, were rigorously established to ensure the selected studies' relevance and integrity. The initial procedure involved filtering, which focused on titles and abstracts, culminating in the preliminary selection of 52 studies. After eliminating duplicates and applying exclusion criteria, the number of relevant studies was refined to 33.

The evaluation phase involved meticulously analyzing the complete texts and implementing the Quality Checklist proposed by Kitchenham [7]. Specifically, the evaluation criteria for this checklist focused on: (a) the clarity and relevance of the research question to airport drone detection; (b) the rigor of the study's methodology and experimental design; and (c) the robustness and clear presentation of the results and conclusions. This process resulted in the careful selection of 25 papers. The chosen documents focus strictly on solutions for identifying drones, specifically in airport environments. It was essential that the studies presented practical implementations of these frameworks in drone recognition activities and were recent publications from the last ten years to ensure the timeliness and relevance of the analyzed results.

The selected studies were notable for their methodological rigor, precision in presenting techniques, solid statistical analyses, and logical interpretations. Only investigations subjected to peer review and published in high-reputation journals were accepted. Manuscripts identified as abstracts, opinions, or editorials, which do not present new data or structured analyses, were removed from the analysis.

During the exploratory phase, it was noted that while numerous articles highlight drone detection at airports as a critical security measure, most lack a specific focus on this environment in their practical applications or results. This misalignment justified a high rate of exclusion, reinforcing the importance of our rigorous filtering process to isolate studies directly applicable to airport-specific challenges.

Although the initial search yielded a large number of studies, the strict application of inclusion, exclusion, and quality criteria resulted in a final set of 25 publications. This number is considered sufficient and representative of the state of the art for several reasons. First, the exclusive focus on airport environments eliminated a significant volume of more generic research. Second, the requirement for practical experimental results and peer review ensured that only the most methodologically rigorous studies were included. Consequently, these 25 studies constitute the core of high-quality research that is directly applicable to the specific problem of drone detection in airports over the last decade.

3. Results

The reviewed literature covers a range of detection methodologies, including acoustic, computer vision (camera-based), radiofrequency (RF), radar, and multimodal systems. Each technique presents a unique profile of advantages and limitations for identifying and tracking UAVs in the critical airspace of airports. Our analysis reveals a diversity of strategies employed to mitigate the threats posed by unauthorized drones, while also underscoring the persistent challenges in achieving effective and reliable detection.

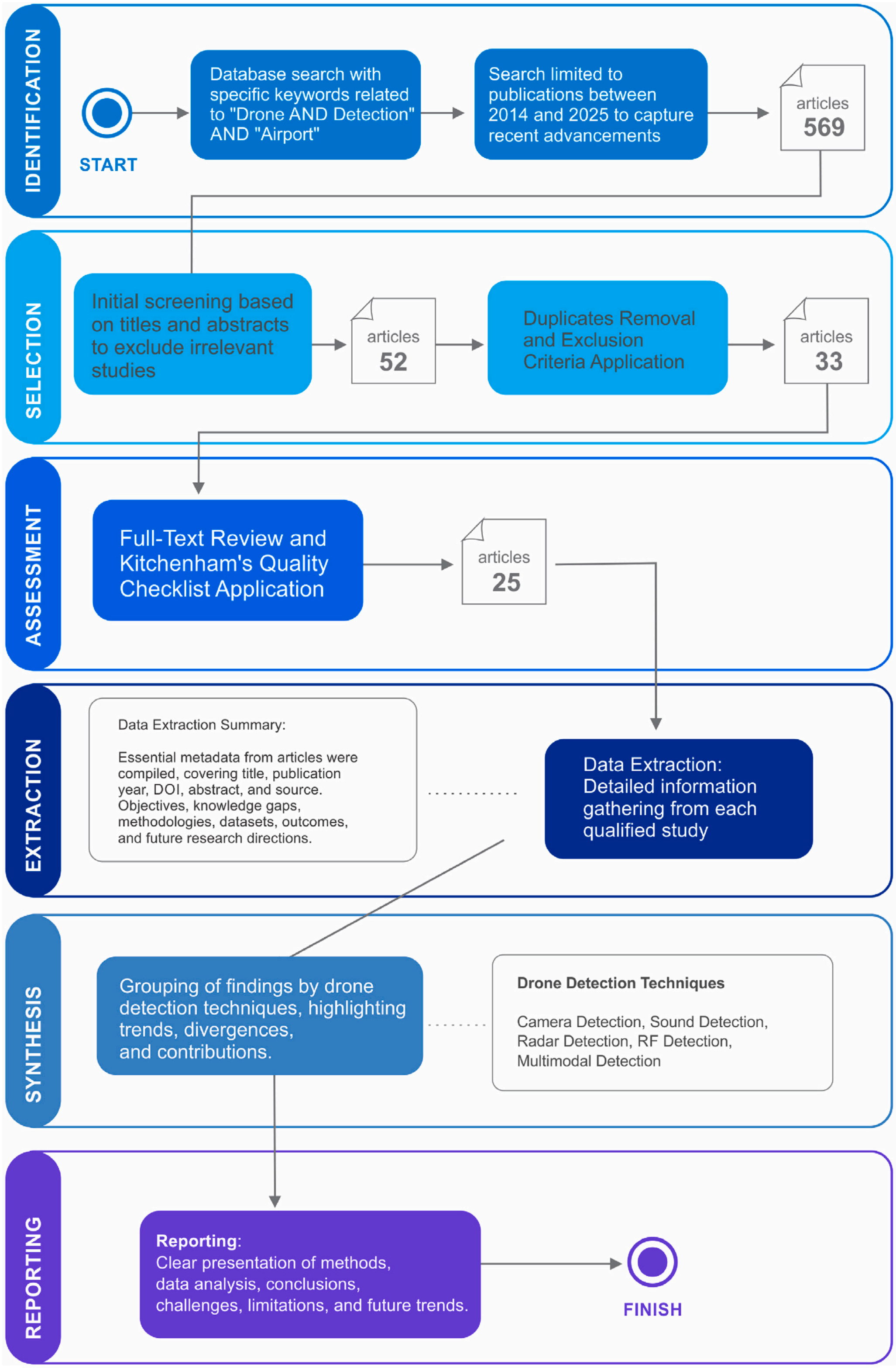

Fig. 1. Systematic review diagram based on the Kitchenham methodology.

Sound detection

Fig. 2 illustrates the procedure for drone detection using acoustic technology. Initially, a microphone captures the sound waves emitted by the drone. These waves undergo an analysis to identify the drone's specific sound frequency. Subsequently, the identified frequency is transformed into a spectrogram, a visual representation that shows the intensity of the various frequencies of the sound emitted by the drone over time. The final step involves using a deep learning model to process the spectrogram and verify the presence of a drone, resulting in a binary response indicating whether the captured sound indeed belongs to a drone (detected: yes/no).

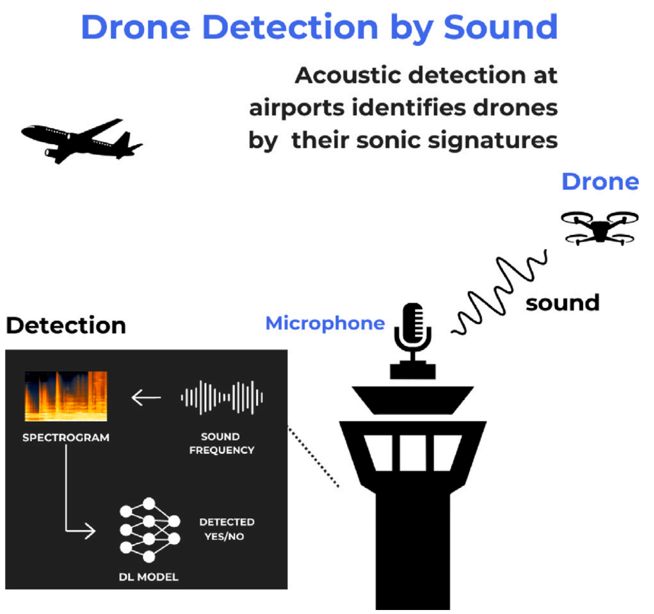

Fig. 2. Process flow for acoustic drone detection. A microphone captures sound waves, which are converted into a spectrogram. A deep learning model then analyzes the spectrogram to classify whether the sound originates from a drone.

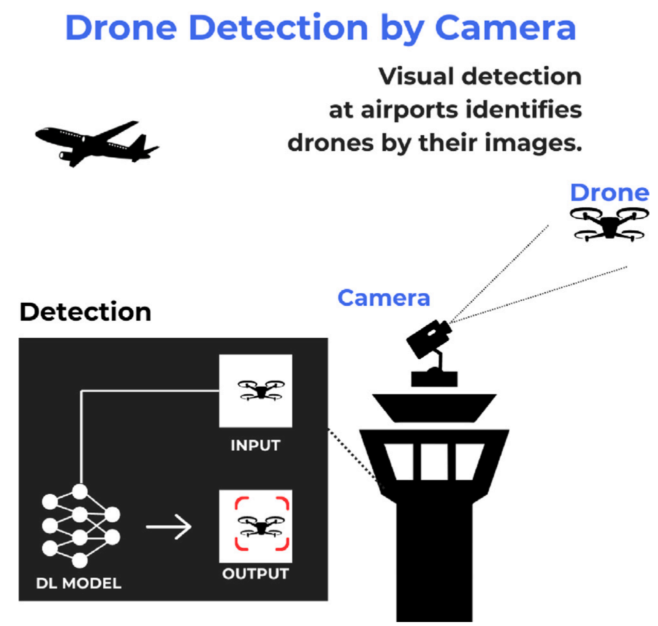

Fig. 3. Diagram of a visual drone detection system. Cameras capture images of the airspace, which are fed as input to a deep learning model (e.g., YOLO, ResNet) trained to identify drone shapes and characteristics.

Studies in this area demonstrate both the potential and the significant challenges of acoustic detection. The study by [8] proposed using Hidden Markov Models (HMM) to classify drone sounds. However, effectiveness is severely limited by ambient noise. Experimental data from other studies quantify this limitation: Busset et al. [9] report a maximum detection range of 160 to 290 m, depending on the drone model, in outdoor conditions with traffic noise. Similarly, Cummings et al. [10] achieve a detection accuracy of 92% at a close range of 30 m, but this performance dropped to 76% at 60 m, with false alarms from sources like wind and lawn equipment being a significant issue. Therefore, while acoustic detection is a low-cost option, its application in airport environments is severely restricted by the high levels of background noise and its short effective range.

Camera detection

A common finding from the reviewed studies is that camera-based detection, leveraging computer vision and deep learning, is a highly effective method for identifying drones [11–16]. As illustrated in Fig. 3, the typical workflow involves capturing airspace images, which are then processed by a deep learning model trained to recognize the specific shapes and characteristics of drones. The model's output then indicates the presence and location of one or more drones within the captured image.

A significant portion of the research focuses on the application and comparison of various deep learning architectures, particularly for the challenging task of differentiating drones from birds. For instance, several studies explore the YOLO (You Only Look Once) family of models, with [13] evaluating the efficacy of YOLOv4 [17] against Faster R-CNN [18], while [15,19] implement and optimize versions of YOLOv5. Concurrently, other studies utilized architectures based on Residual Networks (ResNet) [20], such as the use of ResNet50 by [16] and ResNet-18 by [11]. These studies commonly employ pre-processing and data augmentation techniques [21] to enhance model accuracy. Other innovative approaches include the use of high-frame-rate video analysis to detect the signature of rotating propellers [12] and the proposal of distributed camera clusters to cover extensive areas [15].

Other studies, such as [14,22], explore methodologies involving Generative Adversarial Networks (GANs) (combining real and synthetic images) and recurrent convolutional neural networks, respectively, highlighting the use of topological data analysis and the leveraging of temporal flight information for drone identification.

Additionally, [19,23] have advanced detection techniques by incorporating super-resolution modules and optimizations specifically for resource-limited devices. The use of an ESRGAN module by [23] and the adaptation of YOLOv5 to create Light-YOLOv5 in [19] illustrate the continuous evolution and adaptation of detection methodologies to address emerging challenges in drone surveillance at airports.

Recent advancements continue this trend of model optimization. For example, Chen et al. [24] propose an enhanced YOLOv8 model, named YOLOv8-AIR, specifically for airport environments. By integrating a Vision Transformer (ViT) module and multi-scale feature fusion, their model showed significant improvement in detecting small targets like drones and birds, while maintaining a lightweight architecture suitable for real-time deployment.

In a similar vein, Serageldin et al. [25] also focus on enhancing YOLOv8 performance for real-time UAV detection. Their contribution include the creation of a large-scale, custom dataset with over 27,000 images. By optimizing the model's training process with a cyclic learning rate scheduler, they demonstrated a substantial improvement in detection accuracy, further highlighting that advancements in training methodologies are as fundamental as architectural changes for pushing the state of the art in visual detection.

A fundamental challenge for camera-based detection systems is the performance variation between daytime and nighttime operations. Most of the discussed deep learning models, primarily trained on daytime image datasets, experience a drastic reduction in efficacy under low-light conditions. To overcome this limitation, the integration of infrared (IR) or thermal cameras is strategic. As observed in field tests [26], the use of EO/IR (Electro-Optical/Infrared) sensors is a common practice in multimodal systems to ensure 24/7 surveillance. IR cameras do not rely on visible light; instead, they detect the heat signature from a drone's motors, making them effective in darkness, fog, or smoke. However, the resolution of thermal imaging can be lower, and differentiating drones from other heat sources, such as birds, remains a challenge.

Regarding the limitations of camera-based detection, studies such as [11,16] identify computational efficiency and real-time processing as primary challenges. They underscore the need for robust systems that can effectively handle malicious attacks and adapt to diverse environmental conditions.

Similarly, [12,15] show limitations in detection under adverse weather conditions and in the requirement for a clear line of sight between sensors and drones, respectively. These issues highlight the importance of developing detection methods that can operate effectively in diverse environmental scenarios and overcome physical obstacles that may impede drone visibility.

On the other hand, [14,23] address concerns about the costs associated with collecting new data and the reliance on specific hardware for real-time validation. These limitations highlight the need for cost-effective and flexible detection methods that can be tailored to various equipment and operational conditions.

Finally, the study by [19] highlights challenges associated with the lack of hardware specifications and the absence of details on image preprocessing, indicating a need for clarity and precision in the design and description of drone detection systems.

To advance this technique in future study, [16] suggests exploring advanced deep learning techniques, such as reinforcement learning and attention models, while also emphasizing the importance of integrating cybersecurity mechanisms into edge devices like Raspberry Pi or Arduino, thereby improving the accuracy and efficiency of drone detection systems.

In parallel, [13,15], and [11] highlight the need to evaluate additional deep learning models and emphasize the importance of enriching datasets with a greater diversity of objects to improve the accuracy of drone detection. They recommend expanding the research to encompass more complex and varied scenarios, including adverse weather conditions, to enhance the robustness of detection systems and minimize false positives while also improving the efficiency of real-time processing.

[12] emphasizes the importance of exploring machine learning architectures that consider unique features, such as the signature induced by the rotation of drone propellers, to improve detection in various environments.

Furthermore, studies like [14,22], and [23] suggest expanding the research scope to include a broader variety of drone models and flight scenarios. They encourage exploring sophisticated deep learning techniques and specialized neural networks to improve generalization and efficiency. Specifically, these studies recommend incorporating reinforcement learning and other advanced machine learning methods to tackle the complex challenges of drone detection in diverse environments.

Finally, the proposal of [19] highlights the need for continuous model optimization to reduce resource requirements, pointing towards a trend of more efficient and versatile detection systems.

RF detection

Drone detection using radio frequency (RF) leverages the signals emitted by drones and their controllers to identify and locate uncrewed aircraft. This technique enables covert, long-range detection and is effective even in limited visibility conditions.

As illustrated in Fig. 4, this process begins with capturing the RF signals emitted by the drone using a strategically positioned antenna. These signals are then transmitted to a receiver, where a deep learning model for effective drone detection processes them. The deep learning model analyzes the patterns of RF waves to distinguish between drone signals and other types of signals present in the airport environment.

In the study by [27], an advanced method for classifying drones based on their radio frequency (RF) signatures is investigated using a deep residual convolutional neural network (DRNN). This method enables the passive detection of drones, even without a direct line of sight, thereby extending its analysis to situations involving multiple drones and varying wireless channel conditions and drone speeds. At the core of the methodology, the DRNN is fed spectrograms transformed from RF signals and employs a residual layer architecture to mitigate common problems of vanishing or exploding gradients, thereby facilitating deep learning and efficient classification. Features like max-pooling, global average pooling, and a fully connected layer work together to shape the model's final classification capability, which is operationalized through the Keras and TensorFlow machine learning platforms.

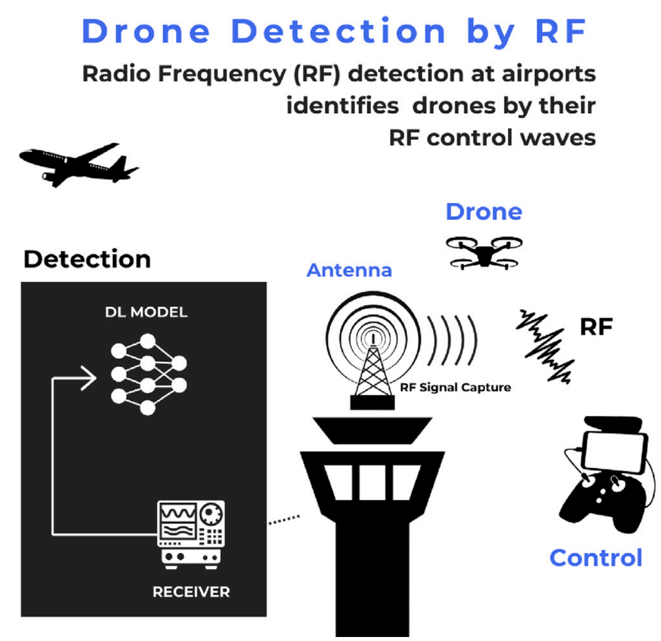

Fig. 4. Conceptual diagram of RF-based drone detection. An antenna captures radio frequency signals, which are processed by a receiver and analyzed by a deep learning model to distinguish drone communication signals from other ambient RF noise.

In [28], a method was developed based on transforming the video control signal of drones using the Short-Time Fourier Transform (STFT) to obtain time-frequency-energy characteristics. To optimize the analysis, Principal Component Analysis (PCA) was employed to reduce the dimensionality of the RF feature data. These data were then used to train machine learning algorithms, specifically the Support Vector Machine (SVM) and K-Nearest Neighbor (KNN), to classify the presence and number of intruding UAVs. The method validation process included testing in an environment configured with four quadcopters and their respective remote controllers, using signals captured by a USRP B210 SDR receiver.

In the study by [29], the URANUS framework was introduced for real-time drone detection and classification using data from Radio Frequency/Direction Finding systems and radars. The system applied preprocessing techniques like Standard Scaler and Label Encoder and combined a Multilayer Perceptron neural network for classification with a Random Forest model for coordinate determination. The URANUS infrastructure enabled immediate processing and analysis of multiple data sources, ensuring efficient drone identification. The study utilized a specific dataset that contained UAV flight information, including location data and distinctive drone characteristics.

In the study by [30], a method based on radio frequency (RF) signatures was proposed for drone classification using a deep residual convolutional neural network (DRNN). The aim was to enhance passive drone detection in various environments, addressing challenges such as the lack of a direct line of sight and multipath and Doppler frequency variations. The study utilized tools such as Keras and TensorFlow, along with hardware, including the USRP X310 and OmniLOG 70600 antenna, as well as commercial drones and a WiFi router for testing purposes. Their proprietary dataset comprised RF signals from nine drones and a WiFi signal, all operating in the 2.4 GHz band, which introduced variations through AWGN noise and simulated multipath channels.

Building on this, the challenge of maintaining classification accuracy in realistic, non-ideal conditions was addressed by Podder et al. [31]. Their study evaluates the impact of noise and multipath fading on a lightweight CNN designed to classify UAVs from RF signals. The study confirms the high performance of deep learning in clean conditions, but more importantly, it demonstrates that the model retains a high accuracy even when the signals are degraded by simulated real-world interference, highlighting the robustness of the RF fingerprinting approach.

From a hardware and deployment perspective, RF systems present significant practical challenges. Most of the reviewed research utilizes specialized hardware, such as Software-Defined Radios (SDRs)—for instance, the USRP X310 and B210 models cited in the reviewed studies [28,30]—and high-performance antennas. While effective, these components represent a higher cost than simple camera setups. The primary deployment challenge, especially in large areas like airports, is the necessity for a network of multiple sensors. As pointed out in field tests [26], achieving precise localization through multilateration for effective airport coverage would require not just 4–6 sensors, but realistically more than 20. Such sensor density increases not only the hardware cost but also the complexity of the network infrastructure and the computational demand for real-time data processing.

Several limitations were identified in studies addressing drone detection via radio frequency (RF), revealing recurring challenges in detecting and classifying these devices. Research conducted by [27,30] highlights shared concerns about the ability of models to distinguish signals in scenarios where frequencies overlap. This situation underscores the need for further investigation to enhance the effectiveness of detection methods in environments characterized by highly complex radio frequency (RF) signals.

Meanwhile, this study emphasizes the potential integration of computer vision techniques to enhance detection and classification, suggesting a future direction of combining RF approaches with visual analysis for more accurate drone identification.

On the other hand, Xu et al. [28] face different limitations, focusing on the potential loss of UAV signals due to hardware constraints such as bandwidth and sampling rate. This study highlights the need for developing more robust signal feature extraction methods that can overcome RF hardware deficiencies, particularly in environments where wireless noise may obscure weaker drone signals.

Meanwhile, the study by [29] implies limitations related to the quality and quantity of input data and environmental conditions, which can impact the accuracy and effectiveness of the URANUS framework. This observation highlights the importance of collecting high-quality data and tailoring detection systems to operate effectively in diverse environmental conditions.

Together, these limitations highlight key challenges in drone detection, including the need to handle complex signal scenarios, overcome RF hardware limitations, develop effective feature extraction methods, and ensure the robustness of detection systems across various environmental conditions. The convergence of these concerns highlights the need for integrated approaches that combine various technologies and analytical techniques to enhance the efficient and accurate detection of non-cooperative drones.

For future research in drone detection, [27] aims to improve analysis in frequency overlap scenarios, with a particular emphasis on integrating computer vision techniques to enhance drone detection, localization, and classification. This approach suggests a shift towards using mixed methods combining RF signals with computer vision insights to create a more robust and accurate detection system.

On the other hand, [28] specifically focuses on deploying SDR detection arrays to improve the capture of long-range drone signals, indicating a more signal-capture-oriented approach to recognizing distant drone patterns. This interest in expanding the detection range complements the goals of [27,30], extending the effectiveness of detection systems beyond current limitations.

Additionally, [29] approaches the issue from a different perspective, suggesting the need to improve the accuracy and effectiveness of detection systems in varying environmental conditions and explore new drone detection technologies. This direction emphasizes adapting and developing technologies capable of operating in a wide range of conditions, complementing the efforts of other studies to create more adaptable and comprehensive detection systems.

Thus, while the studies outline different aspects of drone detection, from improving signal capture to integrating new technologies and analysis methods, they collectively point to a rapidly growing research field with a common goal of developing more efficient and adaptable detection systems to address the increasing threat posed by non-cooperative drones.

Radar detection

The drone detection process using radar can be described through a simplified illustrative diagram, as shown in Fig. 5. Initially, the radar emits a pulse of radio waves (*Pulse*) that propagates through the environment until it encounters an object, such as a drone (*Drone*). When it hits the drone, the pulse is reflected (*Echo*) and then captured again by the radar. This reflected information is crucial for identifying and tracking the drone, especially in sensitive areas like airports, where monitoring the airspace is essential for safety. The sequence of events is schematically represented: pulse emission, reflection off the drone, and radar echo detection.

The practical implementation of radar technologies in airport environments faces multiple challenges, primarily the complexities associated with signal interference, detecting small objects against significant background noise, and distinguishing between drones and other small aircraft or moving objects, such as birds. Recent innovations in radar technology, such as millimeter-wave and passive radar systems, are designed to mitigate these obstacles. Additionally, there is a need for broad area coverage and adaptation to the rapid technological evolution of UAVs, which can affect monitoring effectiveness.

[32] focus on differentiating between birds and drones using the DJI Phantom 3 model, employing Random Forest to analyze radar data and extract movement descriptors, addressing a common challenge in airport environments. On the other hand, [33] implemented a Passive Radar system using DVB-T signals to simultaneously monitor various target sizes, including those with a small radar cross-section (RCS), highlighting the need to collect data in real-world scenarios without relying on AI.

[34] expand the approach by integrating multiple sensors, such as Surface Movement Radar (SMR) and Millimeter Wave Radar (mmWave), to develop a Multispectral Drone Detection System (MSDD), aiming for a comprehensive solution without the need for AI. This methodology contrasts with the one proposed by [35], which employed long-term integration with digital radar and techniques such as Keystone Transforms (KT) and Enhanced Fractional Fourier Transform (EFRFT) to detect low-altitude drones in complex environments.

Similarly, [36] develop an L-band staring radar to improve detection sensitivity in electromagnetically saturated environments, such as airports, using continuous 3D surveillance for more effective detection. This approach is similar to that used in [37], which employ the Aveillant Gamekeeper radar to identify small drones at considerable distances, also highlighting the importance of using machine learning classifiers, like decision trees, to improve the distinction between drones and false targets.

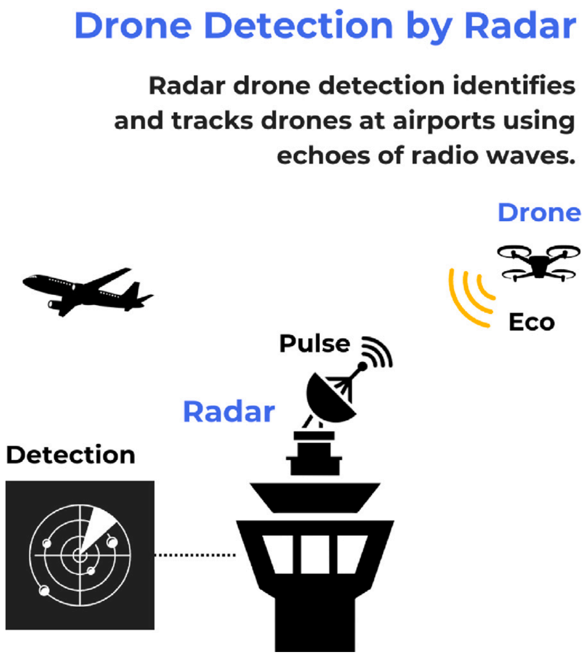

Fig. 5. Principle of radar-based detection. The system emits a radio pulse (*Pulse*), which reflects off the drone as an *Echo*. The radar captures this echo to determine the drone's location, speed, and trajectory.

While varied in their methods and specific technologies, these studies illustrate a common trend in seeking improvements in drone detection. Each addresses different aspects of identifying non-cooperative UAS in controlled and open environments.

Several of the reviewed studies provided results from real-world deployments and field tests, offering valuable insights into radar performance. For instance, the test campaign by Heidger et al. [26] at the Frankfurt and Munich airports revealed that the tested radars performed best between 0.7 and 3 km, with a maximum range of 5 km, but struggled with a high rate of false targets (>50%) and incorrect classifications (>75%). In another field trial, Jahangir & Baker [37] used an L-band radar and reported positive outcomes, with a track probability of update exceeding 80% and a positioning error of less than 25 m. Additionally, Martelli et al. [33] demonstrated the viability of a passive radar at a military airport, detecting a drone at approximately 3 km while simultaneously tracking a commercial aircraft at over 200 km.

In the studies analyzed, a clear division is observed in the application of machine learning techniques for drone detection: [32,37] integrated machine learning methods, such as Random Forest and decision tree classifiers, respectively, highlighting the use of machine learning to enhance drone classification and identification. In contrast, [33,34] focus on non-machine learning approaches, using systems based on Passive Radar and combining multiple sensors without the aid of learning algorithms. This landscape reflects different drone detection strategies, underscoring a range of methods, from purely sensory approaches to data-informed and machine learning solutions.

Airport radar systems struggle with interference, weak reflections from drones, and similar objects masking detections. Additional problems include difficulty differentiating drones from other small mobile entities and limitations in coverage. Integration, costs, legality, and privacy also challenge the effectiveness of detection, necessitating the combination of multiple technologies for efficient results. [32] notes the dependency on tracking accuracy and the difficulty of differentiating targets with uniform movement patterns. This challenge is also reflected in the need, identified in [33], to perform experimental validations to confirm theoretical hypotheses and address sensor performance limitations. Similarly, [34] emphasizes the importance of developing and validating systems in real operational contexts, highlighting the complexity of integrating data from multiple sources. This issue is paralleled by [35], which underscores the need to explore drone detection in cluttered maritime environments and the dependency on specific radar technologies.

Furthermore, [36] addresses the need for more extensive analyses to validate the robustness and effectiveness of the radar system under varied environmental conditions and against a broader spectrum of drones, a limitation that aligns with the observations of [37], which point to the need to expand testing to more challenging environments, including urban operations, for a better evaluation of the system's KPIs.

These limitations indicate a convergence in the areas of improvement necessary for radar detection, suggesting that significant advances can be achieved through an integrated approach considering a broader range of operational scenarios and sensing technologies.

The perspectives for future research indicated in the reviewed studies present various complementary and expanded directions. For example, [32] suggests exploring multi-scale features and the fusion of motion information with radar echo signatures, which can be interconnected with the recommendation from [33] about integrating Passive Radar systems with active systems, addressing challenges such as the suppression of ghost targets. This collaborative approach could enhance target classification accuracy in different surveillance environments.

Additionally, [34] highlights the importance of conducting additional tests in real operational environments and developing advanced algorithms for data analysis, which complements the direction suggested by [35] to test the proposed method in various clutter environments, especially maritime ones. These recommendations converge on the idea of adapting and validating technologies across different operational scenarios.

On the other hand, [36,37] emphasize the need to conduct more tests under different environmental conditions and with a wide range of drones to validate the effectiveness of detection systems. The emphasis here is on diversifying testing conditions and improving classification algorithms to distinguish drones by type and intent, reinforcing airspace management. These approaches indicate a clear trend towards enhancing radar technology continuously and applying more sophisticated machine learning algorithms, aiming for more accurate and contextual identification of UAVs. .

Multimodal detection

Multimodal approaches in drone detection offer significant advantages in terms of accuracy, reliability, and coverage. By integrating various systems such as radar, acoustic, visual, and radio frequency sensors, accuracy is increased, and the chances of false positives and negatives are reduced [38].

Multimodal drone detection at airports is an advanced technique that integrates multiple sensors to effectively and accurately identify drones. As demonstrated in the image, this process involves combining signals captured, for example, from RF antennas and images collected by cameras, which a deep learning model then analyzes. Fig. 6 illustrates the synergy between different sensory technologies for drone identification. In the example, a deep learning model processes a combination of camera input data (Input Cam) and RF signals captured by the antenna, determining the presence of a drone at airports.

The redundancy provided by the diversity of technologies ensures greater reliability, allowing for continuous detection even if one of the modes fails. Additionally, different sensors can cover various areas and altitudes, offering more comprehensive protection against drones in different environments [9]. Adaptability to environmental characteristics and resilience against technological countermeasures by drones further enhance the effectiveness of detection. Lastly, despite the initial costs, the multimodal approach can result in long-term savings by minimizing false alarms and optimizing responses to genuine threats. It presents a

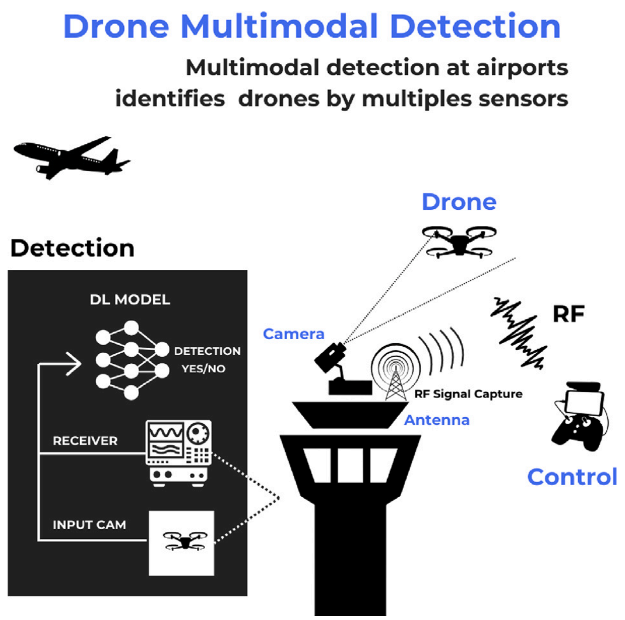

Fig. 6. Example of a multimodal detection process. Data from multiple sensors, such as a camera (Input Cam) and an RF antenna, are fused and fed into a deep learning model to provide a more reliable and accurate detection decision.

robust strategy to address security challenges in critical areas such as airports.

In the study by [26], the performance of Drone Detection Systems (DDS) was analyzed for identifying and tracking non-cooperative UAS in large infrastructures like airports, using diverse technologies such as phased array radar, RF detection, EO/IR sensors, and laser for distance measurement, all integrated through the DDS Mission Control Tools (MCT). Tests were conducted at Frankfurt and Munich airports, applying predefined drone flight scenarios to assess the DDS under real-world conditions. Location data were collected via GPS loggers to establish a precise comparison with the detections made. The performance of the DDS was quantitatively and qualitatively compared to real data, allowing an in-depth evaluation of its capability in airport environments and highlighting the utility of the Multi-Sensor Data Fusion (MSDF) process in generating accurate estimates of drone trajectories.

The study by [10] adopted a distinct methodology, focusing on the combination of acoustic and RF signals for drone detection, starting with classification by Support Vector Machines (SVM) and advancing to processing by a six-layer Convolutional Neural Network (CNN), with the addition of an RF detector to reduce false positives. This research favored acoustic detection due to its reduced cost and adaptability, enhancing the approach with a CNN for greater accuracy. The system's testing was conducted in a real-world environment, an outdoor amphitheater, using a dataset of over 10,000 recordings of drones from various models. The combination of acoustic and RF signals, initially processed by SVM and subsequently by a detailed CNN, provided an efficient method of drone identification, demonstrating the approach's potential in minimizing false alarms while maintaining accurate detection.

Despite their theoretical advantages, real-world implementations of multimodal systems face significant practical challenges in calibration, synchronization, and data fusion. The simple graphical overlay of data from different sensors, without true fusion, was a limitation observed in field tests, where often a single sensor ended up dominating the detection process. Effective multi-sensor data fusion (MSDF) requires advanced association algorithms to create a single, cohesive track from multiple sources. Furthermore, accurate synchronization of data over time is essential; if data from different sensors do not correspond to the same time and location, machine learning algorithms may learn incorrect correlations, thereby compromising accuracy. Sensor calibration, to ensure all systems operate in a common coordinate framework, adds another layer of deployment complexity, alongside the high costs and computational demands required to process multiple data streams in real time.

Table 3
Summary and comparison of drone detection methods in airport environments.

Detection	Studies	Own Dtset	Public Dtset	Use ML	No ML
By sound	1	1	0	1	0
By cameras	12	9	3	12	0
By RF	5	5	0	4	1
By radar	5	3	2	2	3
Multimodal	2	2	0	1	1
Totals	**25**	**20**	**5**	**20**	**5**

In the study of [26], several limitations were identified in the effectiveness of drone detection and tracking. These include variability in performance among different DDS systems tested, challenges in detecting non-standard UAS or those operating under adverse flight conditions, and the need to integrate multiple sensors and advanced data processing technologies to monitor large areas, such as airports, comprehensively. These limitations underscore the challenges associated with providing adequate coverage and adapting to the diverse shapes and behaviors of drones.

On the other hand, the study by [10] highlight distinct limitations associated with the use of detection technology based on acoustic and RF signals. The main concerns include dependence on a specific set of training data for the effectiveness of the CNN, necessitating constant retraining to adapt to new sources of false alarms, and the limitation of the detection range that can restrict its applicability. Additionally, aesthetic issues of detection devices emerged as a limitation in sensitive environments.

Both [10,26] outline distinct pathways for future advancements in drone detection. [26] recommends enhancing multi-sensor data fusion systems and applying artificial intelligence, such as convolutional neural networks, to improve the detection and classification of UAS in complex environments like airports. In contrast, [10] focuses on automatically updating training data to enhance accuracy, reduce false alarms, and explore aesthetically pleasing camouflage techniques. Both studies emphasize the importance of continuous innovation and adaptation to new threats and challenges in airport security and drone detection, underscoring the need for advanced technology and adaptable approaches to address emerging challenges in detecting non-cooperative UAS.

As a synthesis of the explorations conducted on drone detection methods in airport environments, Table 3 presents a compendium of the studies analyzed, highlighting the diversity of approaches and technologies employed. Methodologies range from acoustic signals to multimodal systems, reflecting the dynamics and complexity inherent in the challenge of effectively monitoring airspace in critical zones. Each technique, discussed in detail in the studies, brings its specific contributions and limitations, some of which are dependent on proprietary datasets and others that leverage public datasets to train advanced Machine Learning models. Integrating various detection methods underscores the need for comprehensive and adaptable surveillance, emphasizing the importance of continuous innovations to ensure security against unauthorized drone presence. The conclusion of this section highlights not only current advancements but also directs future research towards incremental improvements and emerging technologies, aiming to overcome adversities and ensure adequate and resilient protection of airport spaces.

In addition to analyzing the performance of existing methods, this systematic review also identified several research gaps and opportunities for future study in each detection modality. Table 4 synthesizes

Table 4
Summary of identified research gaps per detection method.

Detection technique	Identified research gaps and future directions	Key Refs.
Acoustic	• Developing advanced filtering algorithms to overcome high ambient noise in airports. • Improving detection range, which is currently very short. • Creating models that can automatically update their libraries to recognize new drone sound signatures and reject new types of background noise.	[8,10]
Camera (Visual)	• Enhancing performance in adverse conditions (e.g., night, rain, fog) through better sensor fusion (e.g., with IR) and algorithms. • Creating larger, more diverse, and publicly available datasets to improve model generalization. • Developing more efficient and lightweight models for deployment on resource-constrained devices.	[19,24,25]
RF	• Designing robust methods to handle signal interference and frequency overlap in the congested RF spectrum of airports. • Integrating RF data with other sensors (e.g., cameras) to improve classification and reduce false positives. • Improving the detection range and localization accuracy of passive RF systems.	[28,30,31]
Radar	• Applying advanced Deep Learning algorithms, which is a significant gap, to improve the classification between drones and other small objects like birds. • Improving performance in highly cluttered environments (e.g., urban and maritime contexts). • Developing better data fusion techniques for radar echo signatures with other sensor data.	[32,35,37]
Multimodal	• Developing robust, real-time, and low-latency data fusion algorithms. • Solving practical challenges of sensor calibration and time synchronization. • Creating public, large-scale, and synchronized multimodal datasets to facilitate the training and benchmarking of new models.	[26,38]

these main challenges, highlighting the areas that require further investigation to increase the robustness and applicability of drone detection technologies in airport environments.

To consolidate the findings of the 25 studies, Table 5 presents a comparative summary of performance metrics for the five main technology categories, highlighting a clear trade-off between high-performance and high-accessibility systems. On one hand, **Radar** and **Radio Frequency (RF)** based technologies stand out for their superior range and robustness. Radar systems demonstrate detection capabilities at very long ranges, from 5 km to over 10 km [35,36], while RF detection achieves classification accuracy exceeding 90% [29–31]. On the other hand, **Camera (Visual)** and **Acoustic** approaches are notable for their low cost, with implementations available for a few hundred dollars [10], and high processing speeds, with visual systems reaching up to 170 FPS [19]. However, these latter techniques are more susceptible to environmental conditions, such as background noise and poor lighting.

Multimodal approaches emerge as the most promising solution to overcome these compromises, fusing data from multiple sensors to achieve the highest levels of precision, with positioning errors below 1.5% of the range in some systems [38] and near-zero false alarm rates from certain components [10]. This robustness, however, generally implies greater cost and integration complexity. It is necessary to note that the values presented in the Table 5 are a summary of the literature, and real-world performance, particularly in complex airport environments, can vary significantly due to factors such as electromagnetic interference and background clutter.

4. Conclusion and future studies

This systematic review has synthesized and analyzed the primary technologies for drone detection in airport environments, revealing a field with both mature solutions and significant opportunities for innovation. The analysis of 25 curated studies confirms that no single technology is a panacea, as a clear trade-off exists between performance, cost, and practicality. The findings presented here serve as both a foundational guide for immediate security enhancements and a strategic roadmap for future scientific research.

4.1. Conclusion and practical implications

For airport operators and security professionals seeking immediate solutions, the key takeaway is that a multimodal approach is the most robust strategy currently available. The selection of specific technologies should be driven by a risk-based assessment of the airport's unique environment and budget. For critical airspace zones requiring the highest level of security, a combination of radar and RF systems offers the best performance in terms of range and reliability, despite the higher cost. For broader perimeter monitoring or in lower-budget scenarios, a combination of visual cameras – enhanced with IR capabilities for 24/7 operation – and acoustic sensors can provide a cost-effective initial layer of defense. The practical challenge remains the effective fusion of data from these sensors to minimize false alarms and provide actionable intelligence to security personnel.

Finally, the widespread deployment of drone detection systems raises important ethical and legal questions that cannot be overlooked. Systems equipped with high-resolution cameras and RF sensors may, by their nature, indiscriminately capture data, affecting the privacy of not only malicious operators but also the general public and airport staff. As some studies have noted public concern about the intent of drone pilots and potential privacy invasions [10], questions regarding who has access to this collected data, how it is stored, for how long, and for what other purposes it could be used demand a clear governance framework. To ensure public trust and prevent "function creep" – where a security tool becomes a mass surveillance tool – the implementation of these technologies must be accompanied by robust and transparent privacy and data handling policies that align with data protection laws.

Table 5
Comparative summary of performance metrics for drone detection techniques.

Technique	Typical accuracy	Detection range	Latency/Speed	Estimated cost
Acoustic	Performance varies significantly with noise. Reported accuracy ranges from 60%–92%, dropping sharply with distance [10]. Other studies focus on classification feasibility [8].	Short range, typically between 160 m–290 m [9]. Some advanced systems tested up to 1300 m [38].	Fast. Capable of real-time processing, with acoustic imaging up to 60 FPS reported [9].	Low. Can be built with consumer-grade microphones for a few hundred dollars [10].
Camera (Visual)	High in optimal conditions. Reported metrics include: mAP@0.5 from 75.3% to as high as 98.7% [13,24,25], and precision up to 93.8% [19].	Medium to Long. Effective up to 1–2 km [13], with some systems detecting specific drones at 3.5–5 km [26].	Very Fast. Real-time capable, with speeds from 20 FPS on embedded systems (Jetson Nano) [22] to 170 FPS on GPUs [19].	Low to Medium. Can be implemented with low-cost webcams and processing boards [12,15].
RF	Very High for known protocols. Classification accuracy reported as high as 90%–99% in both ideal and noisy conditions [29–31].	Long. Often implied to be >3 km, though not always tested at maximum range in the reviewed studies [30].	Fast. Capable of real-time detection, but specific latency values are not consistently reported [29].	Medium (implied).
Radar	Good to High. Overall classification accuracy reported as >85% [32]. Probability of Detection (PD) measured between 80%–92% [36,37].	Very Long. Consistently reported ranges of 5 km [36], with some advanced systems capable of detecting drones at >10 km [35].	Very Low. Systems operate with fast update rates, typically around 0.25 s–0.5 s per detection [33,36].	High. Generally cited as >$100,000 [10].
Multimodal	Highest accuracy due to sensor fusion. Positional error reported as low as <1.5% of range [38]. RF component can yield 0% false alarms [10].	Variable and typically Long. Depends on the combination of fused sensors (e.g., up to 5 km) [26].	Variable. Can be higher due to data fusion. One study reported 6 s for acoustic-to-optical activation [38].	Variable. Can be very low (~$400) or Very High, depending on the system [10,26].

Note: Values are synthesized from the literature reviewed and can vary significantly based on specific models, deployment environment, and drone characteristics. Some values are qualitative ("Low", "High") as specific numbers were not always reported.

4.2. Future research directions

For the research community, this review highlights several critical long-term challenges and opportunities, as summarized in Table 4. Future studies should prioritize three main areas. The first is the development of more sophisticated **algorithms**, particularly the application of advanced deep learning models to radar data for improved drone-versus-bird classification and the creation of adaptive filters to mitigate noise in acoustic data. The second is the advancement of **system integration**, focusing on robust, low-latency data fusion techniques and solving the practical challenges of sensor synchronization and calibration in complex multimodal systems. Finally, the most significant barrier to progress is the lack of large-scale, publicly available, and perfectly synchronized **multimodal datasets**. The creation of such benchmark datasets is essential to train and validate the next generation of AI-driven drone detection systems, ensuring they are resilient, reliable, and effective in real-world airport environments.

CRediT authorship contribution statement

Sanderson Oliveira de Macedo: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mauro Caetano:** Validation, Supervision, Formal analysis, Conceptualization. **Ronaldo Martins da Costa:** Validation, Supervision, Formal analysis, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

The authors conducted all research and wrote the manuscript. However, during the preparation of this study, the authors utilized Grammarly tools to enhance text concordance and employed GPT-4 by OpenAI for assistance with text structure. After using these tools/services, the authors reviewed and edited the content as necessary and took full responsibility for the publication's content.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sanderson Oliveira de Macedo reports financial support was provided by Federal Institute of Education, Science, and Technology of Goias (IFG). Sanderson Oliveira de Macedo reports a relationship with IFG, that includes: employment. The remaining authors declare that they have no conflicts of interest, financial or personal, that could have influenced the study reported in this paper.

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Data availability

Data will be made available on request.

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