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DETECTION AND CLASSIFICATION OF AIRBORNE OBJECTS BASED ON MACHINE LEARNING: CURRENT STATE OF RESEARCH

The article provides a comprehensive overview of modern technologies for detecting airborne objects. It emphasizes the use of machine learning (ML) methods to improve the accuracy and reliability of surveillance systems. The study is relevant due to the growing number of airborne objects that threaten civil and military infrastructure. Traditional detection methods also have limitations in adverse weather conditions or when radio interference is present. Intelligent technologies, capable of recognizing object behavior patterns and functioning under uncertainty, are especially important in this context.

The primary approaches to detecting aerial objects are analyzed, including radio frequency monitoring, radar analysis, electro-optical and thermal imaging surveillance, and acoustic monitoring. Their advantages, limitations, and specific applications are identified. Special attention is paid to systems that use ML algorithms for automated object recognition and classification. Thanks to its ability to independently detect patterns in data without human intervention, machine learning ensures high accuracy and reduces the influence of the human factor.

The paper summarizes the results of recent studies that demonstrate the accuracy of detection in test environments, the ability of systems to adapt to new scenarios, and the improvement in reliability through multisensor integration. It is shown that combining data from different sensors – radar, EO/IR, acoustic, and radio frequency – in conjunction with ML algorithms creates the basis for building adaptive airspace monitoring systems.

The conclusions emphasize that the effectiveness of combating air threats depends on the ability of systems to integrate heterogeneous data and use intelligent analysis algorithms, which paves the way for the creation of accurate, flexible, and reliable means of detecting new types of airborne objects.

Keywords: detection; classification; machine learning; deep learning; radio frequency monitoring; radar surveillance; electro-optical and infrared sensors (EO/IR); acoustic detection; feature extraction; target tracking; multi-sensor integration; embedded systems.

ЗДОРИК НІКІТА, ЯНКОВСЬКИЙ ОЛЕКСАНДР

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ВИЯВЛЕННЯ ТА КЛАСИФІКАЦІЯ ПОВІТРЯНИХ ОБ'ЄКТІВ НА ОСНОВІ МАШИННОГО НАВЧАННЯ: СУЧАСНИЙ СТАН ДОСЛІДЖЕНЬ

У статті подано комплексний огляд сучасних технологій виявлення повітряних об'єктів із акцентом на використання методів машинного навчання (ML) для підвищення точності та надійності систем спостереження. Проаналізовано основні підходи до виявлення повітряних об'єктів – радіочастотний моніторинг, радіолокаційний аналіз, електрооптичне й тепловізійне спостереження, а також акустичний контроль. Визначено їхні переваги, обмеження та специфіку застосування. У роботі узагальнено результати сучасних досліджень, які демонструють досягнення точності виявлення у тестових середовищах, здатність систем адаптуватися до нових сценаріїв і підвищувати достовірність завдяки мультисенсорній інтеграції.

Ключові слова: виявлення, класифікація; машинне навчання; глибоке навчання; радіочастотний моніторинг; радіолокаційне спостереження; виділення ознак; трекінг цілей; мультисенсорна інтеграція; вбудовані системи.

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Introduction

Unmanned aerial vehicles (UAVs) pose new security challenges, stimulating the development of various technologies for detecting these airborne objects. The most common detection methods include radio frequency (RF) signal analysis, radar, electro-optical/infrared (EO/IR) imaging, and acoustic sensors. Each method has its strengths and weaknesses, and modern anti-UAV systems often employ multiple sensors to achieve better coverage. Recently, machine learning (ML) techniques have been applied to improve UAV detection and classification across all of these modalities. Additionally, software-defined radio (SDR) platforms are frequently utilized for flexible and cost-effective radio frequency-based UAV detection.

Below, these methods are analyzed and compared in terms of effectiveness and accuracy, highlighting current systems, strengths, and limitations.

Main part

Effective object detection is a crucial step in developing modern monitoring, security, and automated environmental analysis systems. The choice of detection method largely determines the accuracy, response speed, and resistance of the system to interference. There are several basic detection methods (Fig. 1), each with its own advantages

and limitations.

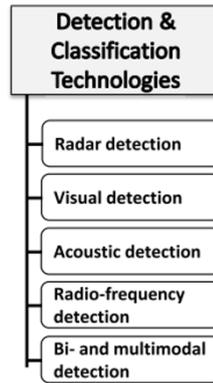


Fig. 1 – Classification of detection methods

Radio frequency (RF) detection. In all detection methods, ML has become a vital tool for improving detection accuracy and reducing false alarms. ML algorithms learn the characteristic patterns of airborne object signatures in RF spectra, radar reflections, images, or audio, providing more reliable identification than manual thresholds.

Radio frequency-based drone detection relies on tracking radio communications between the drone and its controller, as illustrated in the algorithm (Fig. 2). It typically intercepts uplink control signals or downlink telemetry data in frequency bands characteristic of UAVs (e.g., 2.4 GHz, 5.8 GHz)[1, 2].

By analyzing signal characteristics or protocols, a radio frequency sensor can detect and identify the presence of a drone long before it becomes visible to the naked eye.

Modern radio frequency analyzers can even pinpoint the location of the airborne object's controller using multiple receivers to determine the angle of arrival or triangulation.

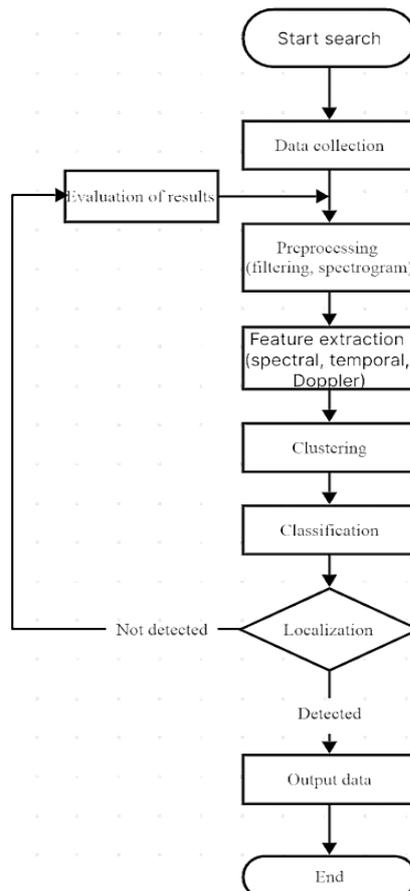


Fig. 2 – Radio frequency method algorithm

This method works in all weather conditions and lighting, as it does not depend on visual contact. Radio frequency sensors are relatively simple and cost-effective. They can be deployed as a network of receivers covering large areas. These sensors can detect and track multiple drones simultaneously, provided each drone maintains communication. They can even classify drone makes/models by their signal “fingerprints.” The system may also determine the pilot's location, as it can sometimes geolocate the controller's transmitter [3].

The main limitation is that radio frequency methods cannot detect airborne objects that do not emit radio signals [3]. Autonomous airborne objects flying along pre-programmed routes or in radio silence mode will evade pure radio frequency detectors. Detecting RF signals also requires knowledge of the communication protocols and frequencies of the target aerial objects, and new or modified signal types (e.g., special telemetry, frequency hopping) may not be recognized, rendering the system “blind” to these threats [4].

In urban or crowded radio frequency environments, these sensors face interference and multipath issues that reduce accuracy [4]. Determining the exact direction of a signal can be difficult without an antenna array, and cheaper radio frequency sensors can only detect presence without precise localization.

The range of sensors is limited compared to radar (the practical range of radar detection is often from several hundred meters to 1-2 km for small airborne objects, depending on transmission power and line of sight) [5].

Other disadvantages include dependence on weather conditions and terrain, as heavy rain or obstacles can weaken signals (although not as much as optical/infrared).

Thus, radio frequency sensors are ideal for early warning and identification when airborne objects use known radio communications, but they are vulnerable to missing uncooperative airborne objects and to noise in challenging conditions.

RF analyzers are widely used in commercial anti-drone systems as the first line of detection. For example, the Dedrone platform utilizes passive radio frequency sensors to continuously scan for airborne object control signals, enabling the classification of an airborne object and its model using a signature library (DedroneDNA). It claims a detection range of up to ~1 mile for consumer airborne objects [5]. In addition to commercial solutions, military-grade radio interception systems (e.g., Rohde & Schwarz ARDRONIS) can not only detect and locate airborne object controllers, but also jam or intercept communications when authorized to do so [6].

Overall, radio frequency detection is popular due to its low cost and ease of deployment, making it suitable for protecting critical infrastructure and events where many commercial airborne objects are operating. The need to update signal databases and the inability to counter silent threats necessitate the combination of radar with other sensors for a more reliable solution [7-10].

Radar detection. Radar is an active sensing technology that detects airborne objects by reflecting radio waves. It determines target range, altitude, and speed. Modern radars remain essential for medium- and long-range surveillance, providing reliable detection of even small, challenging targets, such as multirotors, thanks to their high resolution and advanced processing [11].

Machine learning in the radar domain is utilized to analyze Doppler and micro-Doppler features (caused by the operation of the propeller group), enhance interference filtering, and improve the accuracy of “drone/bird” classification [11, 12]. In practice, this is implemented by constructing time-frequency maps and classifying them using neural networks, or by training models on trajectory/track features [12].

This method can detect any type of airborne object without requiring interaction or radiation, making it agnostic to the design of the drone, provided that it reflects or interferes with radio waves [13].

Radars function continuously, regardless of rain, fog, or smoke, giving them a clear advantage over optical methods. They monitor extensive areas, with single systems often covering several kilometers. Additional strengths include real-time target tracking, precise speed and trajectory measurement, simultaneous tracking of multiple targets or swarms, and distinguishing airborne objects using unique features like the micro-Doppler effect, which detects subtle signal modulations from rotor blades.

Significant drawbacks of this method are that small airborne objects have a very low radar cross section (RCS) [13, 14], which means that the reflected signal is weak and easily lost in interference or noise, and without special processing, bird detection can dominate drone detection or be mistaken for drones, so radars often require complex algorithms or machine learning to classify targets based on their radar signatures, adding complexity and cost.

Radars require direct visibility of the target, as terrain or buildings can block low-flying objects from detection, creating a problematic ground-level dead zone. Additionally, radar signals need careful management to prevent interference with other systems.

Radar is widely used in the military and security sectors to detect drones. For example, airbase defense systems utilize 3D radar as the primary sensor for detecting intrusions at long range. There are specialized anti-drone radars, such as the Robin radar systems (ELVIRA, IRIS), which utilize micro-Doppler processing to distinguish between drones and birds, or Echodyne's compact AESA radars for drone detection [16].

Modern systems, such as DroneHunter and Obsidian, use radar to detect and track aerial objects, even distinguishing drone swarms by their unique signatures. Since small aerial targets are difficult to distinguish, radar systems increasingly integrate ML classifiers to differentiate drones from birds, insects, or noise.

For example, researchers trained a decision tree model on simple radar track characteristics (such as target altitude, velocity changes, etc.) [14]. The probability of detecting small airborne objects improved to 88%. The false alarm rate was reduced to zero in their tests. These results illustrate the power of ML in significantly reducing false positives by learning the differences in how airborne objects move or reflect signals. Neural networks are also utilized in various other applications. They analyze micro-Doppler radar signatures or polarimetric radar data to classify airborne objects versus birds, achieving near 100% accuracy in controlled experiments. On the RF side, ML is used for radio frequency fingerprinting. This involves analyzing unique modulation or spectral characteristics of an airborne object's signal.

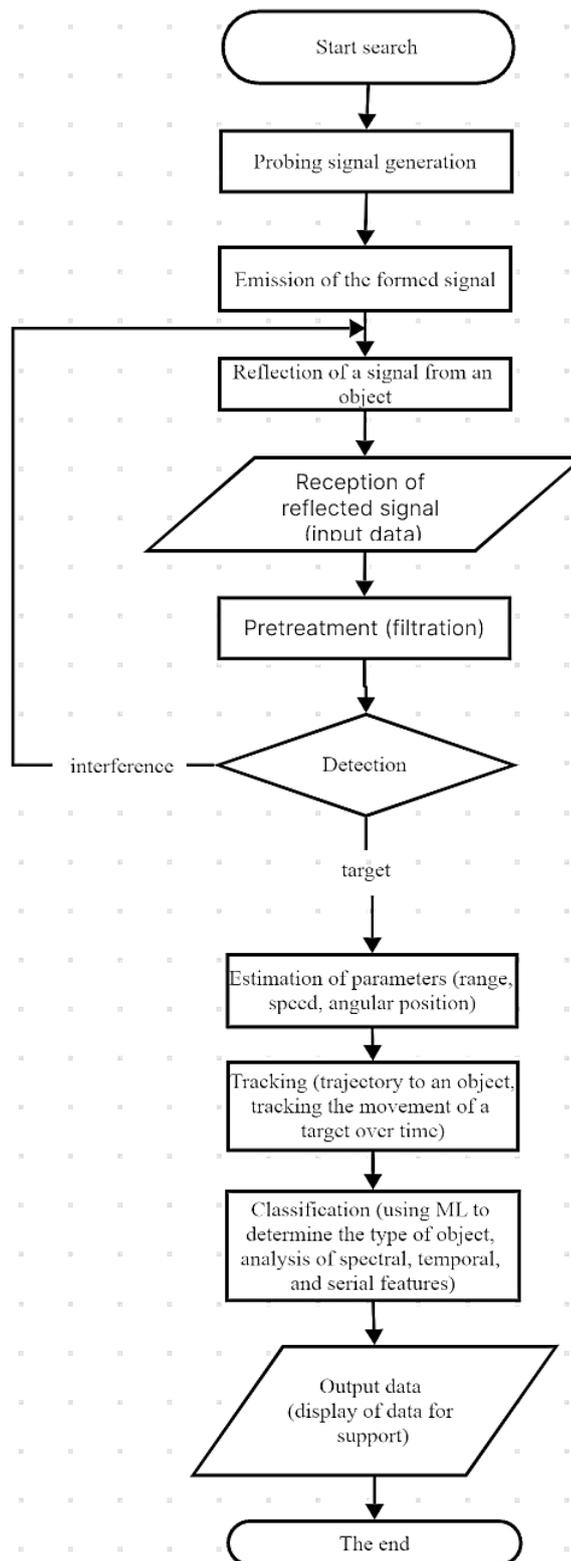


Fig. 3 – Algorithm of the radar detection method

ML is also used to detect anomalies in the RF spectrum that indicate the transmission of a signal from an airborne object amid background noise.

Optical (EO/IR) detection. Optical detection uses visual spectrum cameras (electro-optical – EO) and thermal imaging infrared cameras (IR) for visual detection of airborne objects. These sensors primarily perform video surveillance of the sky: the EO camera detects the shape or movement of an airborne object against the background, while the IR camera identifies the heat signature from engines or batteries (Fig. 4).

The optical channel (video surveillance in the visible range) and the infrared channel (thermal imaging sensors) provide a high level of interpretability: when an object is detected, the system can provide visual confirmation, class

assessment, and additional attributes (shape, dimensions, nature of movement) [20], [21]. Another advantage of EO/IR is its ease of integration with tracking modules and situational awareness tools.

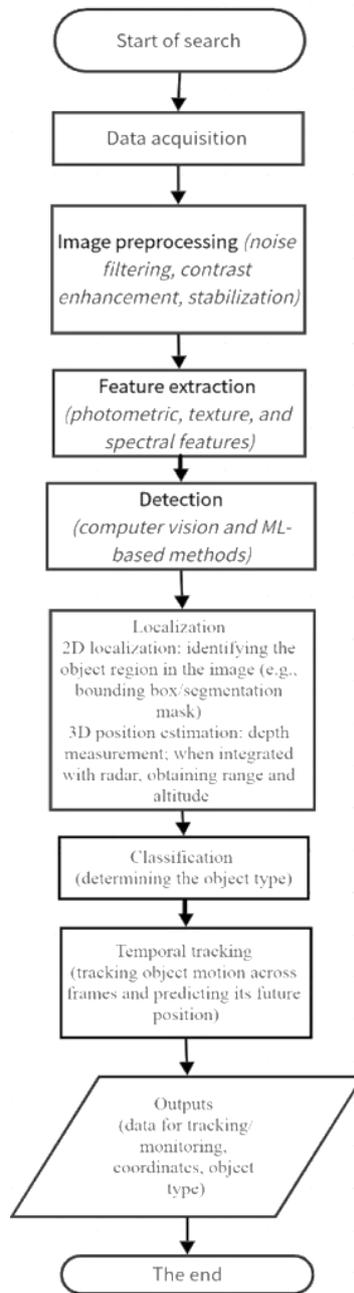


Fig. 4 – Algorithm of the optical detection method

Optical methods are passive (simple observation), but with modern image processing technologies (Fig. 5) and computer vision, they can be effective, especially for identifying and assessing unmanned aerial vehicles.

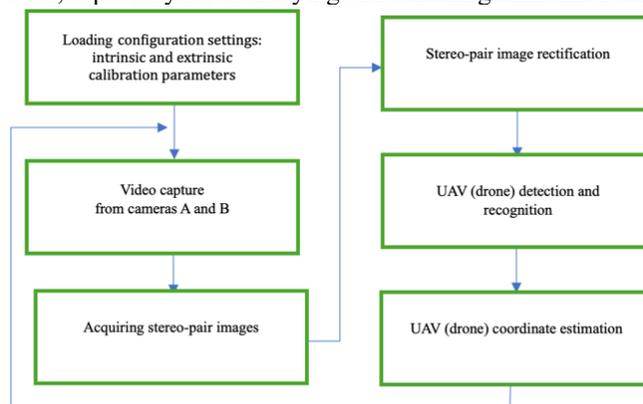


Fig. 5 – Image processing algorithm

Modern ML approaches in EO/IR are based on object detectors (CNN-based detection) and tracking over time. To increase robustness, training is performed on various data sets, as well as specialized “drone-vs-bird” benchmarks that focus on the problem of false positives [20, 24]. The advantages of this method are that EO cameras provide high-resolution images or videos, which can be crucial for identification.

Unlike radar, a daylight camera can confirm the exact model of an aerial object, detect its payload (e.g., if it is carrying a package or weapon), or record its behavior [23]. Thermal imaging IR cameras can detect drones at night by seeing the heat emitted by engines or electronics, and can also operate in certain low-visibility conditions (light fog) where visible cameras do not work. EO/IR covers a wide part of the spectrum (visible in the long-wave infrared range) to maximize the chances of detecting a drone [24].

Cameras can be controlled by other sensors, as many systems use radar or radio frequency to command a pan-tilt-zoom (PTZ) camera to magnify the image and visually track an aerial object. Computer vision and machine learning play a major role – algorithms can detect a small moving dot of an aerial object in video frames and distinguish it from birds or airplanes [23].

The disadvantages of this method are determined by its dependence on direct visibility and favorable environmental conditions, lighting, and contrast, and it can be “blinded” by glare or bright sunlight [25].

In practice, conventional cameras can detect an aerial object the size of a DJI Phantom at a distance of several hundred meters; beyond this limit, it may be too small for reliable detection or recognition without a special lens, and the range of IR cameras is limited by the need for temperature contrast between the aerial object and the background, as a small electric aerial object may emit almost no heat, or the environment may reduce the contrast, leading to missed detections [26].

Optical systems usually provide only two-dimensional information. It is hard to determine the distance to an airborne object with a single camera. Stereo cameras or a mix of EO/IR cameras can estimate distance [27]. Cameras may also mistake birds, balloons, or moving clouds for real objects. AI can filter out many of these cases, but it is not 100% reliable, especially when an aerial object fills only a few pixels on the sensor.

In general, optical methods are indispensable for identification – after detecting an aerial object using radar or a radio frequency sensor, it is optical means that provide the necessary visual image for confirmation. However, due to their limitations, they are rarely used as the sole detection mechanism, especially when it comes to long distances or circular surveillance.

Computer vision is now inextricably linked to ML – the most advanced methods of detecting objects in video use convolutional neural networks (CNN), and researchers are considering visual detectors specific to aerial objects [20]: for example, an approach based on CNN combined with motion compensation achieved an accuracy of about 84–86% on videos with aerial objects.

These trained models outperform simple motion detection, especially in distinguishing aerial objects from birds or clouds [22, 25]. The challenge lies in obtaining sufficient training data of aerial objects at different distances and backgrounds. Nevertheless, ML-based visual detection is promising, and many modern systems already use AI-based video analytics to alert for aerial objects rather than relying on human observation.

Acoustic detection

Acoustic detection utilizes arrays of microphones to detect the characteristic sounds of propellers and motors from aerial objects. Airborne objects, especially multi-rotor ones, produce a typical sound caused by blade rotation and engine vibrations, which mainly lies in the audible range from tens of hertz to several kilohertz, making it possible to detect them with acoustic sensors against the background of ambient noise (Fig. 6) [32], [38].

By using multiple microphones, the system can perform spatial processing (beamforming) to determine the direction of the sound source, and in some configurations, it can also estimate the position of the target by triangulation in a network of spaced acoustic nodes [34], [35], [37]. To identify airborne objects, signature libraries and classification algorithms are often used to distinguish between typical UAV noise profiles and part of the background environment [31], [33].

Passivity and invisibility are significant advantages of this method, as acoustic sensors do not emit signals and do not create radio interference with other systems. Their portability also simplifies the rapid deployment of microphone arrays in the field [35], [37], [38]. The acoustic channel is useful for detecting objects that do not have active radio communication or are inconspicuous to radar, as rotating propellers form stable spectral components that systems can use to select useful signals and partially filter out “ground noise” [33], [36]. Arrays can also be scaled to form a distributed network of acoustic nodes, increasing coverage and improving direction/position estimation accuracy [35], [37].

Detection of airborne objects that do not emit radio signals or have low radar visibility, since any airborne object with rotating propellers generates a certain amount of noise, as acoustic sensors can often distinguish the true sound of an airborne object from other background noise based on spectral characteristics — they are tuned to the specific frequencies of the motors of aerial objects. This allows ignoring some of the “ground noise” that can interfere with other sensors, so that acoustic arrays can be scaled — creating a network that covers a larger area and allows joint triangulation to determine the location of an aerial object.

The primary disadvantage of acoustic detection is its limited range, as sound intensity decreases rapidly with distance and can be masked by background noise. Consequently, its actual effectiveness depends significantly on the acoustic environment [32], [38].

Weather conditions also affect the detection process, as wind and temperature gradients can alter the trajectory and propagation characteristics of sound waves [38]. A separate problem is the occurrence of false alarms due to sources with similar spectra (such as equipment or other mechanisms) and the difficulty of separating multiple simultaneous sound events when signals overlap [32], [34].

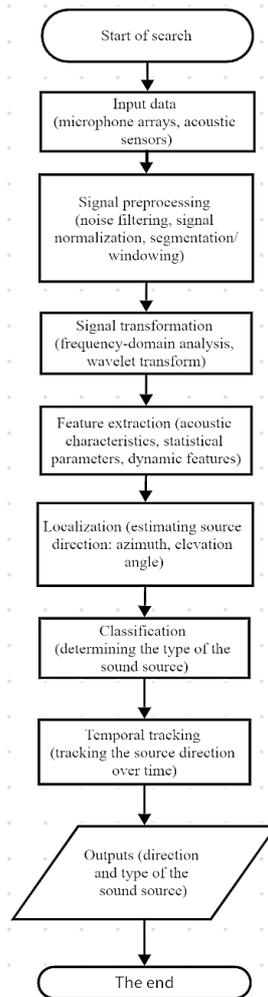


Fig. 6 – Algorithm of the acoustic detection method

Acoustic detection is also vulnerable to false alarms that can occur due to similar sounds, such as lawnmowers or distant helicopters, which can be mistakenly identified as airborne objects if filters are not applied. Additionally, overlapping sounds make it impossible to determine the number of airborne objects. Acoustic detection is used as a component of multi-sensor systems. One of the well-known manufacturers is Squarehead Technology, which has developed the Discovair acoustic array. This array utilizes beamforming and machine learning algorithms to detect airborne objects and filter out background noise.

In practice, acoustic sensors are often integrated into the system so that in the absence of confirmation from an RF or radar sensor (for example, the object does not emit radio frequencies), the acoustic sensor can detect an airborne object at close range, which means that acoustic detection plays a supporting role in covering cases that other sensors may miss [35], [37].

In audio ML, it is used to isolate acoustic signals from airborne objects from ambient sounds [32], [36]. Approaches range from classical (e.g., Hidden Markov Models (HMM) or Gaussian Mixture Models (GMM)) to deep learning (CNN on spectrograms or even audio-based RNN) [32, 34, 36].

The study found that the RNN classifier performed best, with ~80% accuracy, in detecting an airborne object by sound in a 150 m test, while the CNN performed slightly worse at 58% (likely due to the limited training data) [32]. Importantly, performance declined when testing on types of airborne objects not included in the training set, indicating generalization issues [32]. Another team, using SVM with manually created audio features (mid-frequency cepstral coefficients (MFCC), spectral characteristics), achieved 96.4% accuracy in distinguishing air object noise from other ambient noises in a specially selected dataset [33].

This high figure reflects a controlled scenario; accuracy in the real world will be lower due to variable noise levels [32, 38].

Nevertheless, ML is invaluable here—it allows for dynamic filtering of background noise (the system can learn to ignore repetitive sounds, such as a distant highway), focusing on the characteristic acoustic “fingerprint” of an airborne object. As new sound profiles of airborne objects emerge, ML models can be retrained or adapted, making acoustic detection smarter over time.

Combined methods. The use of machine learning plays a major role in combining data from multiple sensors. A complex system can receive data from radar, radio frequency (RF), optical, and acoustic sensors and use a machine learning model to determine whether the detected object is indeed an airborne object.

For example, if the radar sees an object and the acoustic sensor hears something in the same direction, an ML-based data fusion algorithm can correlate this data to increase confidence. Conversely, if the radar sees an object but the acoustic and RF sensors are silent, it may be a bird—a trained model can learn this pattern.

In general, machine learning helps overcome the individual limitations of sensors by learning from data (Fig. 7) and making more nuanced decisions than fixed rules.

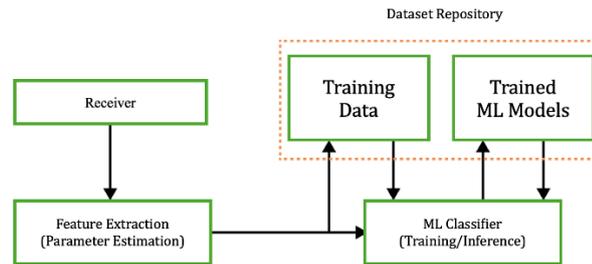


Fig. 7 – Block diagram of the ML-based classification pipeline

A disadvantage of heavy reliance on ML is the need for large amounts of training data. A study (link) noted that many ML-based air object detection studies are not directly comparable due to the lack of common datasets or benchmarks.

Despite these challenges, the trend is clear: future improvements in air object detection are closely linked to advances in machine learning – whether it be better neural network architectures for computer vision, adaptive algorithms in RF analysis, or reliable audio classifiers capable of operating in new noise conditions.

Conclusions

Modern drone detection technologies perform various functions: radio frequency detection provides cost-effective monitoring of drone communications, radar detection provides all-weather tracking at long distances, thermal imaging and infrared imaging provide identification, while acoustics detect silent or low-profile drones at close range.

Machine learning and SDR significantly expand these capabilities, making detection smarter and more adaptive. No single method is perfect; the most powerful systems combine multiple sensors to leverage their complementary strengths.

Continuous advances in sensor hardware, computing power, and algorithms are rapidly improving detection range and accuracy. With the proliferation of drones, the future of drone detection will depend heavily on integrated, intelligent sensor networks capable of early, reliable detection and tracking of drones under any conditions, which will be a decisive first step in protecting airspace from unauthorized drone intrusions.

The above analysis is based on a synthesis of recent research and reviews of anti-drone technologies, including assessments of the effectiveness of radio frequency, radar, optical, and acoustic sensors, machine learning-based detection research, and information on current air defense systems and their sensor integration.

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