international journal of critical infrastructure protection 49 (2025) 100744

Contents lists available at ScienceDirect

International Journal of Critical Infrastructure Protection

journal homepage: www.elsevier.com/locate/ijcip

Advances in UAV detection: integrating multi-sensor systems and AI for enhanced accuracy and efficiency

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ARTICLE INFO

Keywords:
UAV Detection
UAV Classification
Radar Technology
Sensor Fusion
Optical Sensor
Acoustic Sensor

ABSTRACT

This review critically examines the progress in unmanned aerial vehicle (UAV) detection and classification technologies from 2020 to the present. It highlights a range of detection methods, including radar, radio frequency (RF), optical, and acoustic sensors, with particular emphasis on the integration of these technologies through advanced sensor fusion techniques. The paper explores the core technologies driving improvements in detection accuracy, range, and reliability, with a special focus on the transformative role of artificial intelligence and machine learning. These innovations have significantly enhanced system performance, enabling more precise and efficient UAV detection. The review concludes with insights into emerging trends and future developments that promise to further refine UAV detection technologies, ensuring greater security and operational reliability.

1. Introduction

Unmanned aerial vehicles (UAVs) have become increasingly prevalent across sectors such as military operations, commercial delivery, and surveillance. However, their potential misuse—ranging from espionage to terrorist attacks—presents significant security challenges. In response, advanced UAV detection technologies capable of long-range identification have become crucial for safeguarding sensitive areas. Among the primary detection methods are radar, radio frequency (RF) analysis, and optoelectronic and acoustic systems, each with unique strengths and limitations.

Radar-based detection is a leading technique for locating and tracking UAVs by assessing signals to determine both position and velocity. However, radar systems face operational challenges, such as interference from environmental clutter, that can degrade detection accuracy. The positioning of radar installations at higher elevations helps extend their detection range by reducing obstructions from ground-level objects [1–3]. Similarly, RF-based methods leverage electromagnetic signals emitted by UAVs for long-distance detection but suffer from issues related to signal interference and difficulty in pinpointing UAV positions. One of the main drawbacks of RF systems is their limited ability to pinpoint the exact direction of the UAV without extensive observation, which improves accuracy over time [1–3].

Optoelectronic systems, which rely on cameras and sensors, offer precise detection capabilities but are constrained by visibility conditions and environmental factors like haze or precipitation. These systems generally have a shorter detection range than radar but excel in target recognition capabilities [4–5]. Acoustic detection methods, while effective in short-range scenarios, are hindered by background noise in urban environments and struggle with smaller UAVs.

To overcome the limitations of individual detection methods, recent advancements in sensor fusion technologies combine these systems, enhancing accuracy and reliability. This review explores the key technologies developed since 2020 for UAV detection and classification, with a focus on how artificial intelligence (AI) and machine learning (ML) are reshaping the field. These advancements are paving the way for more robust and reliable detection systems, capable of addressing both present and future security challenges.

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https://doi.org/10.1016/j.ijcip.2025.100744
Received 29 May 2024; Received in revised form 3 October 2024; Accepted 9 February 2025
Available online 11 February 2025
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2. UAV detection and recognition technologies

2.1. Technologies for detecting and recognizing UAVs based on radar systems

2.1.1. Description of technologies for detecting and recognizing UAVs based on radar systems

All technologies characteristic of UAV recognition radar systems can be divided into two classifications: by frequency range and by type of modulation (Fig. 1).

Classification by frequency range includes:

- L band [8,10]
- S band [7,10,11]
- C band [12]
- X band [10]
- Ka band [6]
- W band [12]

Classification by type of modulation:

- FMCW (Frequency-Modulated Continuous-Wave) [9,11,12,15,19]
- LFPM (Linear Frequency-Phase Modulation) [10]
- FSK (Frequency Shift Keying) [7]
- LFM (Linear Frequency Modulation) [7]

SFM (Stepped Frequency

In UAV radar recognition systems, a number of technologies can be distinguished that are combined with each other for the purpose of detection and classification:

1. Radar Cross Section (RCS) analysis: Measurement and analysis of the radar cross section of UAVs for their classification and identification [6,9].
2. Machine learning and Deep learning: Application of machine learning and deep learning methods for classification and detection of UAVs based on radar data [15,17,19,20].
3. Micro-Doppler signature analysis: Using micro-Doppler analysis to identify and classify UAVs based on their motion and characteristics [12,14,16].
4. Statistical recognition: Using statistical methods to recognize and classify UAVs based on radar signals [6,9,16].
5. Use of radar spectrograms: Classification of UAVs based on radar spectrograms and analysis of their characteristics [15,17,20].
6. Use of multi-frequency radars: Classification and detection of UAVs using multi-frequency radars and analysis of their micro-Doppler signatures [12,14].

The authors of articles [15,18] use deep neural networks (DNN) to classify UAVs, but with different goals and approaches. The paper [15] focuses on UAV classification based on radar spectrograms using convolutional neural networks (CNN). The focus is on analyzing radar data to identify and classify UAVs.

The operating principle of the technology includes the following stages:

1. Signal recording: Signals from various targets, including unmanned aerial vehicles, are recorded using FMCW radar.
2. Conversion to spectrograms: Recorded signals are converted to spectrograms via Short-time fourier transfer (STFT), which allows visualization of micro-Doppler effects that occur when targets move.
3. Analysis using deep learning CNN: Spectrogram characteristics are analyzed using convolutional neural networks such as ResNet to classify and identify targets based on micro-Doppler signatures.
4. Development of ResNet-SP model: A ResNet-SP model is created with reduced computation but increased accuracy and stability, which facilitates efficient target classification.
5. Model training and performance evaluation: Models are trained on a proprietary radar spectrogram dataset and then their performance is evaluated in real time.

Thus, the authors' technology [15] is based on the use of radar spectrograms and deep learning to effectively classify and identify UAVs based on their micro-Doppler characteristics. The article [18] proposes a hybrid DNN model to classify the intent of unmanned aerial vehicles based on radar data. Here the focus is on determining the intentions and targets of the UAV based on telemetry and radar measurements. The operation of the proposed system can be described in three stages:

- data preparation and radar simulation;
- creation of a hybrid deep neural network;
- network training and testing.

A technology based on RCS analysis for statistical recognition of UAVs at microwave frequencies was proposed by the authors [6]. The main stages of operation of the proposed radar system:

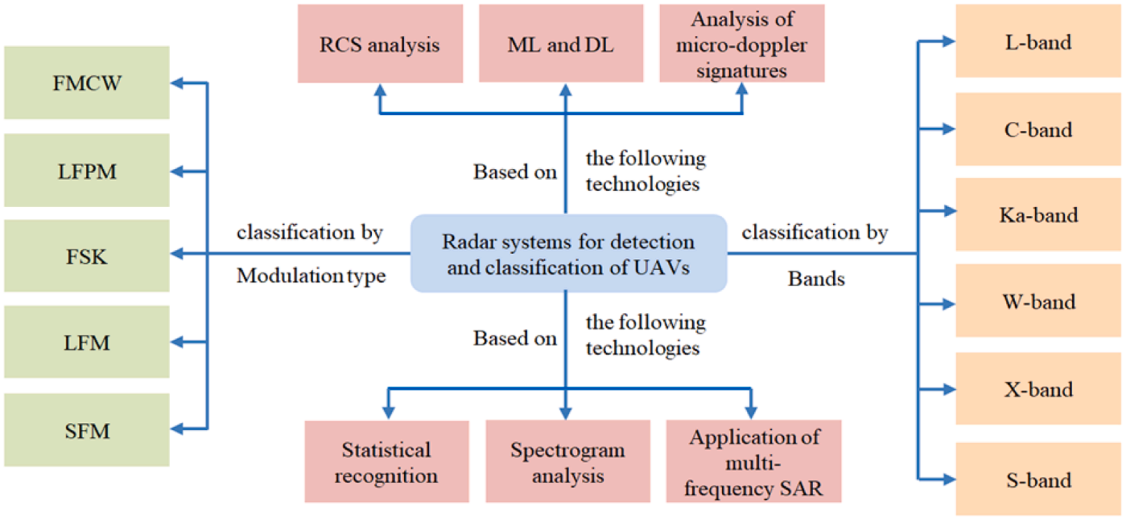


Fig. 1. Diagram of radar systems for detecting and classifying UAVs.

1. UAV RCS measurement: Carrying out RCS measurements of various commercial UAVs at specific frequencies in a special compact band anechoic chamber to obtain information about the reflectivity of target UAVs;
2. RCS Analysis: Analyze RCS data and fit it to various statistical models using maximum likelihood, AIC [define acronym] information criterion and Bayesian information criterion (BIC) methods to select the best statistical models for each type of UAV;
3. Statistical UAV Recognition: Development of a UAV recognition system that estimates the probability of RCS test data belonging to one of the UAV types in the database using the most appropriate statistical distribution selected by AIC and BIC criteria to classify unknown UAVs based on their RCS;
4. Performance Evaluation: Conduct Monte-Carlo analysis to evaluate the effectiveness of the technology and study the influence of signal-to-noise ratio, frequency and polarization on the accuracy of UAV classification.

The system proposed by the authors [13] is based on the use of a bistatic radar operating at 5 G frequencies. Bistatic radar uses two separate devices to transmit and receive signals, allowing it to effectively detect objects that reflect signals. The radar analyzes reflected 5 G signals that do not pass through the line of sight and are reflected from the UAV body. These reflected signals, known as NLOS (non-line-of--sight), help determine the presence of a drone in the surrounding area. Additionally, the system captures received signal strength indicator (RSSI) values, which provide information about the drone's signal strength at various locations. This allows you to determine where the drone is and what its signal strength is at a specific point. The K-Nearest Neighbors (KNN) machine learning algorithm is used to predict the presence of a drone and its location in a 2 × 2 m grid. In order to evaluate the performance of the system, experiments were carried out both indoors and outdoors. The results showed that this technology can effectively detect and localize drones. The data on the accuracy of radar systems for detecting and classifying UAVs based on the technologies described above are presented in Table 1. In [16] the authors presented another performance parameter instead of accuracy - F1. This parameter also takes into account false positive and false negative results, which is relevant in cases of class imbalance in the training data set.

2.1.2. Future directions for research and improvement of technologies for detecting and recognizing UAVs based on radar systems

The future development directions of UAV (Unmanned Aerial Vehicle) detection and classification systems based on radar technologies are quite promising and multifaceted, with several key areas of focus and innovation. These advancements aim to address the growing concerns about the increasing prevalence and potential misuse of UAVs, as well as enhance the overall effectiveness and reliability of these detection and classification systems.

One critical direction is *Enhanced Sensor Fusion*, which involves integrating radar systems with other complementary sensor technologies, such as optical, acoustic, and radio frequency sensors. By combining the strengths of these different sensing modalities, the detection accuracy can be significantly improved, and the number of false positives can be reduced. This holistic approach to sensor integration allows for more comprehensive and robust UAV detection, overcoming the limitations of relying on a single sensor technology [80].

The integration of advanced Machine Learning and Artificial Intelligence algorithms is another key area of development. These cutting-edge techniques can be leveraged to enhance the classification and tracking capabilities of radar systems, enabling more accurate identification of UAV characteristics and behaviors. Real-time data processing and adaptive learning models can further improve the system's performance, allowing for rapid and dynamic adaptations to changing UAV threats and operating environments [81].

Another innovative approach is *the implementation of Classify While Scan (CWS) Technology*. This technique enables simultaneous scanning and classification of detected objects, thereby improving the overall detection performance of radar systems. By seamlessly integrating the detection and classification processes, CWS technology enhances the efficiency and accuracy of UAV identification, providing a more streamlined and responsive solution [82].

Miniaturization and Portability of radar systems is a crucial development direction, as it allows for the deployment of these technologies in a wider range of environments, including urban areas and remote locations. Compact and easily transportable radar systems can be strategically positioned to provide comprehensive coverage and monitoring, addressing the challenges posed by the increasing prevalence of small and low-altitude UAVs.

The concept of Networked Radar Systems further expands the capabilities of UAV detection and classification. By creating a network of interconnected radar systems, comprehensive coverage can be achieved, enabling the effective detection and tracking of low-altitude and small UAVs that may have evaded single, standalone radar systems. This collaborative approach leverages the collective data and processing power of the network to enhance the overall effectiveness of the UAV detection and classification efforts [83].

Finally, *the advancement of signal processing* techniques plays a vital role in improving the ability to distinguish UAVs from other objects, such as birds or manned aircraft. Refined signal processing algorithms can better analyze the unique signatures and characteristics of UAVs, enabling more accurate differentiation and reducing the risk of false detections or misidentifications.

These multifaceted development directions, ranging from sensor fusion and machine learning to miniaturization and networked systems, collectively address the growing challenges posed by the proliferation of UAVs. By harnessing the latest technological advancements, the future of UAV detection and classification systems holds great promise in enhancing the security and safety of our skies.

Table 1
Performance of radar technologies.

Link	Technology	Accuracy
[6]	RCS analysis for statistical recognition of UAVs	At SNR 10 dB: 97.43 %
[7]	Using bispectral slices and the GA-BP neural network	At SNR 3 dB: 90 %
[10]	NeXtRAD multistatic radio system	–
[11]	Machine learning and analysis of FMCW radar data	85.1 %
[12]	Radars of various frequency ranges, machine learning	C-Band: 80.95 % L-Band: 72.5 % K-Band: 86.05 %
[13]	Bistatic radar operating at 5 G frequencies	UAV presence: ~100 % Localization: 75 %
[15]	Deep learning using radar spectrograms that reflect micro-Doppler effects	83.39 %
[16]	Combination of radar data and CNN	F1: 81.6 % ± 1.1 %
[17]	Analysis of target movement characteristics and the use of machine learning methods	85 %
[18]	Hybrid deep neural networks and non-cooperative radars	97.75 %
[19]	Radar platform with FMCW MIMO technology	78.68 %;

2.2. UAV detection and recognition technologies based on RF sensors

2.2.1. Description of UAV detection and recognition technologies based on RF sensors

RF-based systems for UAVs detection and classification (Fig. 2) are capable of operating with high accuracy by integrating the following technologies:

- Passive RF sensing [22];
- Compressive sensing [27];

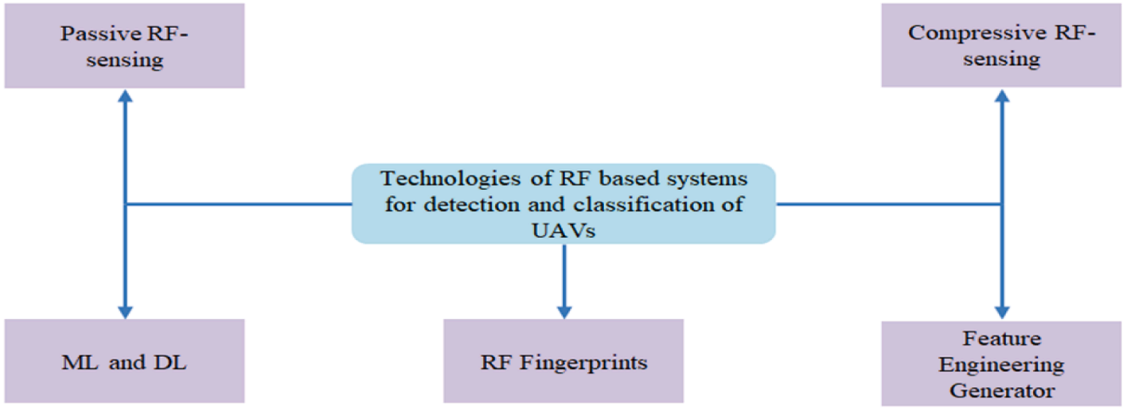


Fig. 2. Diagram of RF-based systems for detecting and classifying UAVs.

- Machine learning and Deep learning [25];
- RF fingerprints [21,26,28,29];
- Feature generation (FEG) [24].

Passive RF sensing relies on analyzing RF signals and using machine learning to recognize preamble patterns, reducing computational costs. Thus, the system is capable of acting as a stand-alone intrusion detector or as part of a distributed sensor network. The drone presence detection process is carried out on-board the embedded computer, and the identification of the drone model can be performed in the data fusion center. Compressive sensing is used to process radio frequency signals to efficiently extract information from these signals with a minimum number of measurements. Deep learning is used to build a neural network capable of detecting and classifying UAVs based on these compressed RF signals. The authors' technology [22] is based on the use of passive RF sensing using a distributed network of sensors to detect and identify UAVs. The system includes several sensors that collect RF signals emitted by drones. The signals are sent to a data center where software-defined radio (SDR) is used to analyze and process the RF signals. Hardware-accelerated time-frequency computing allows for efficient real-time signal processing and identification of UAV-specific characteristics. UAV detection and identification algorithms are configured for high accuracy and low false alarms. After processing the data, the system is able to detect the presence of a UAV, classify its model and transmit information to the operator to take appropriate action. In the article [25], the authors proposed a technology with the development of machine learning based on RF signals. By extracting spectral characteristics from RF signals, a unique RF signature is created for each type of UAV. The XGBoost machine learning algorithm is then applied to analyze these RF signatures to determine the presence of a UAV, its type and mode of operation.

The technology process includes the following steps:

- Extracting spectral characteristics from radio frequency signals that are emitted by UAVs;
- Creation of a unique RF signature for each type of UAV based on the extracted spectral characteristics;
- Training machine learning models using the XGBoost algorithm based on unique RF signatures;
- Evaluation of models for the accuracy of detecting the presence of a UAV, determining its type and operating mode.

A new approach combining Feature Engineering Generator (FEG) and Multi-Channel Deep Neural Network (MC-DNN) methods for detecting and classifying UAVs based on RF signals was proposed by the authors of [24]. This technology includes four stages. First stage: Collection and pre-processing of RF signals. At this stage RF signals received from the UAV are collected. Signals undergo pre-processing, including noise filtering, data normalization and other methods to improve their quality, and prepare for further analysis. Second stage: Feature Engineering Generator (FEG). This step involves extracting key features from preprocessed RF signals, including separating different frequency components, reducing signal similarity, and extracting unique characteristics for each signal type. FEG helps make signals more distinguishable and informative for further analysis.

Third stage: Using Multi-Channel Deep Neural Network (MC-DNN). At this stage, multi-threaded (multi-channel) classification of RF signals occurs based on the extracted features that were obtained using FEG. MC-DNN is trained to recognize different types and flight modes of UAVs. Fourth stage: Detection and classification of UAVs. At this stage, after processing and classifying RF signals using MC-DNN, the presence of unmanned aerial vehicles is detected and classified into types and flight modes. The performance of radio frequency UAV detection and classification systems based on the functionality of the above technologies is presented in Table 2. To evaluate performance, the authors used the Precision, F1, and Accuracy metrics.

2.2.2. Future directions for research and improvement of technologies for detecting and recognizing UAVs based on RF sensors

The development of UAV detection systems based on RF technology is a rapidly evolving field with great potential. As the technology continues to evolve, researchers and engineers are exploring various future directions to improve its capabilities and versatility. Below are seven future directions for the development of RF-based UAV detection and classification technologies.

1. *Improved signal processing techniques.* Future RF-based UAV detection systems will incorporate advanced signal processing techniques to improve detection accuracy and reduce false alarms. Techniques such as machine learning and deep learning are actively used to analyze RF signals more effectively, distinguishing between the unique signatures of UAVs and other RF sources [29]. Using the

Table 2
Performance of RF-based UAV detection and classification systems.

Link	Technology	Performance
[22]	Passive RF sensing	Accuracy at range up to 150m: 99.94 % Accuracy at range up to 350m: 99.38 %
[24]	FEG and MC DNN	Accuracy: 98.4 % F1: 98.3 %
[25]	XGBoost	Accuracy of detecting the presence of drones: 99.96 % Accuracy of drone detection and their type: 90.73 %
[26]	Sequential CNN	Accuracy: 92.5 % F1: 93.5 %.
[27]	DNN, CNN	Accuracy: of over 99 %
[28]	DNN	Accuracy at SNR 0dB: 99 %
[29]	RF fingerprints	Accuracy: 99 %

power of artificial intelligence, these systems can learn to recognize subtle patterns and anomalies in the RF spectrum, allowing for more accurate UAV identification even in complex and cluttered environments.

2. *Integration with other detection technologies.* Combining RF detection with other complementary technologies such as radar, optical and acoustic sensors creates a more robust multi-sensor system [79].
3. *Miniaturization and Portability.* As technology advances, there is a trend towards more compact and portable RF-based detection systems. This will allow for easier deployment in a variety of environments, including urban areas and remote locations. Smaller, lighter, and more energy-efficient systems can be easily integrated into a wide range of platforms such as mobile devices, fixed installations, or even the drones themselves, allowing for greater flexibility and adaptability in UAV detection operations.
4. *Improved Range and Coverage.* Future systems aim to expand the detection range and coverage of radio frequency-based UAV detection. This can be achieved by developing more sensitive RF receivers, using improved antenna designs, and implementing beamforming techniques. By increasing the sensitivity and directivity of RF sensors, these systems can detect UAVs at greater distances, providing a wider surveillance area and allowing for earlier threat identification.
5. *Real-time data processing and analysis.* The ability to process and analyze data in real time is critical to effective UAV detection and response. Advanced signal processing algorithms, high-performance computing, and edge computing capabilities will enable these systems to quickly detect, classify, and track UAVs, providing operators and decision makers with timely and actionable information [79]. As the use of UAVs continues to grow, the need for reliable and robust detection systems becomes increasingly important. Future radio frequency-based UAV detection systems will need to incorporate advances in hardware and software to enhance their performance and capabilities. By integrating faster processors, such as powerful microprocessors or specialized chips, these systems will be able to analyze sensor data and generate alerts faster, allowing for a faster response to potential threats or intrusions. Additionally, the development of more efficient algorithms and signal processing techniques will further optimize the detection and identification processes, increasing the overall accuracy and reliability of the system.
6. *Cybersecurity Measures.* As UAV detection systems become increasingly complex, they will also need to incorporate robust cybersecurity measures to protect against potential hacking and tampering. Ensuring the integrity and security of the detection system will be a key focus, as these systems will be handling sensitive data and critical infrastructure. Advanced encryption protocols, secure communication channels, and comprehensive access controls will be essential to protect the system from cyber threats. Additionally, regular security audits, vulnerability assessments, and continuous monitoring are necessary to maintain the overall cybersecurity of the detection system.
7. *Integration of AI and Machine Learning.* Integration of artificial intelligence (AI) and machine learning (ML) will continue to play a major role in the development of RF-based UAV detection systems. These advanced technologies can aid in pattern recognition, anomaly detection, and predictive analysis, making systems smarter and more efficient. Using AI and ML algorithms, detection systems can learn from past data, adapt to changing operating conditions, and improve their performance over time. This can lead to increased detection accuracy, reduced false positives, and the ability to more effectively anticipate and respond to emerging UAV threats. As these technologies continue to evolve, their seamless integration with RF-based detection systems will be a key focus for researchers and developers.

These future directions highlight the potential for significant improvements in RF-based UAV detection systems, making them more efficient, reliable and secure in a variety of applications such as critical infrastructure protection, airspace security and public safety.

2.3. Optical-electronic systems for UAVs detection and classification

2.3.1. Description of optical-electronic systems for UAVs detection and classification

Optical-electronic systems for UAVs detection and recognition can be classified according to technical means and classification technologies (Fig. 3).

Classification by technical means:

- systems based on optical surveillance cameras [30,31,33,34,35,36];
- optical-electronic systems based on thermal imaging infrared sensors [38];
- UAV detection and classification systems based on laser-optical sensors (LiDAR) [39].
- The following object recognition technologies are also subject to classification:
- Deep learning [30,31,32,33,34,35,36,37,40];

Machine learning [30,34].

The authors of [30] present a method for drone detection using CNN in comparison with support vector machines (SVM) and k-nearest neighbors (KNN). This work proposes two stages.

1. Drone image feature extraction: This step involves analyzing UAV images to extract key features that may be important for their classification. These cues may include the UAV's shape, size, texture, color, and other characteristics that help differentiate the drone from other objects.
2. Training a convolutional neural network on the extracted features: After extracting the key features of the drone images, this data is used for training. The CNN is trained on reference data to learn to recognize and classify drone images based on the extracted features.

The testing phase includes two stages:

1. Classification of new drone images. The trained CNN model is applied to classify the new input UAV images. The model uses the learned features to determine whether the image is a UAV or not.
2. Improving UAV detection precision using CNN: CNN helps distinguish UAV images from bird images, which helps improve UAV detection accuracy. By learning from extracted features and the ability to identify complex patterns, CNN can effectively distinguish objects and improve classification precision.

The results of the research [30] show that CNN outperform SVM and KNN in UAV detection, achieving an accuracy of 95 %.

The article [34] presents a technology for detecting UAVs in video with high accuracy in real time. The authors divide the UAV detection task into two stages: detecting moving objects and classifying them into drones, birds or background.

1. Detection of moving objects. To identify moving objects, the background proofreading method is used, which allows you to select objects that differ from a static background. This method helps to quickly and accurately identify objects that move in a video stream.
2. Classification of objects. Detected objects are classified using a convolutional neural network (CNN) that is trained on a set of images of UAVs, birds, and backgrounds.

Based on the YOLOv5 deep learning model, an autonomous UAV detection system was implemented in [35]. The operating principle of this system includes 4 main components.

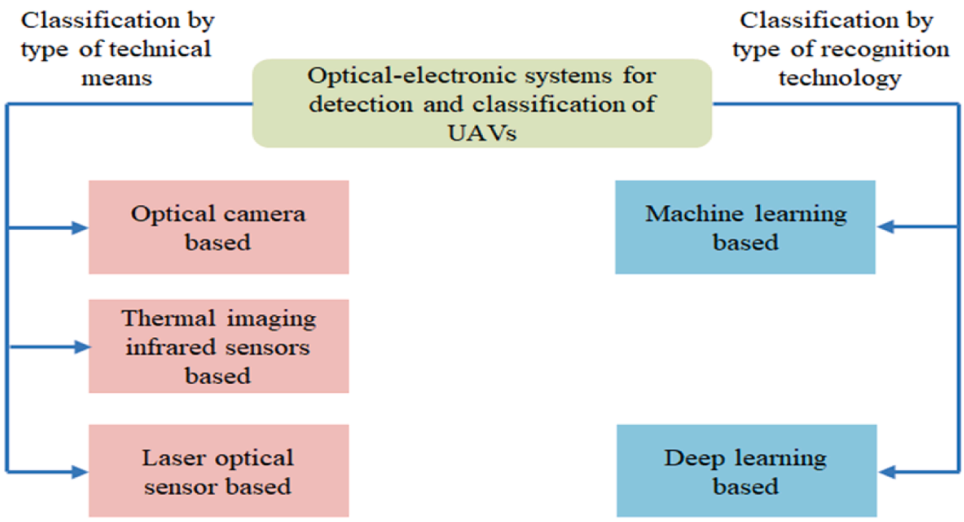


Fig. 3. Diagram of optical-electronic systems for detecting and classifying UAVs.

1. YOLOv5 algorithm: object detection algorithm that works in real time. It divides the image into a grid and, for each grid cell, predicts bounding boxes and object class probabilities. One of YOLO's key advantages is its ability to detect objects quickly and accurately.
2. Model training: To train the model, the authors used pre-trained weights and data augmentation techniques. This allows the model to train on a small data set and prevents overfitting. The model is trained on labeled images of UAVs to learn how to recognize them in the images.
3. Autonomous detection: Once trained, the model can operate autonomously, detecting UAVs in images without the need for human intervention. This allows the technology to be used to automate the UAV detection process in real time.
4. Evaluation of results: After training, the model is evaluated using metrics such as average precision (mAP) and recall to measure its performance and accuracy in UAVs in images.

The results show that YOLOv5 outperformed previous versions of YOLO in UAV detection speed and precision. The technology presented in [38] is based on the integration of three key elements to improve the quality of UAV detection and classification through thermal image analysis.

1. Saliency Cues. Calculating a highlight map helps highlight areas where UAVs are likely to be located in thermal images. This extraction map is combined with the feature map of the Faster-RCNN neural network to improve feature extraction and model training.
2. Sign of enlarged small objects (ESO). The ESO module is designed to magnify small drones in the input image, which helps the neural network detect them better.
3. Data Augmentation Technique. The proposed data augmentation technique makes it possible to create new thermal imaging images of drones from various sources for training a neural network.

The above components work together to provide more accurate and reliable UAV detection in a variety of scenarios and lighting conditions. The technology described in [40] is based on the use of a modified version of the YOLOv8 network for detecting small UAVs.

The authors present an improved detection model that includes additional modules and mechanisms to improve the precision and efficiency of detection. The model architecture introduces an attention mechanism to improve target feature fusion and overall performance for UAV detection. The performance of optical-electronic UAV detection systems described in [30–40] is presented in Table 3. To evaluate performance, the authors used different accuracy metrics, such as Accuracy, mAP, Recall, Precision, F1.

Table 3
Performance of optical-electronic systems for detecting and classifying UAVs.

Link	Detection and classification technology	Performance
[30]	CNN	Accuracy: 95 %
	SVM	Accuracy: 88 %
	KNN	Accuracy: 80 %
[31]	YOLOv4	mAP: 74.36 %
		Precision: 95 %
		Recal: 68 %
		F1: 79 %
[32]	YOLOv2	–
[33]	YOLOv2	mAP: 74 %
[34]	Background proofreading and CNN	Precision: 70.1 %
		F1: 74.2 %
		Recall: 78.8 %
[35]	YOLOv5	mAP 90.40 %
[36]	YOLOv8	–
[37]	YOLOv4	Accuracy: 83 %
		mAP - 84 %
[38]	saliency cues and magnified features on thermal images	mAP – 94.98 %
[40]	YOLOv8	mAP: 95.3 %
	YOLOv7-tiny	mAP: 85 %
	YOLOX-s	mAP: 88.7 %
	YOLOv5-s	mAP: 91.2 %

2.3.2. Future directions for research and improvement of optical-electronic technologies for UAVs detection and classification

Future developments in UAV (Unmanned Aerial Vehicle) detection and classification systems that identify drones using optoelectronic systems (such as video sensors, infrared sensors, and LiDAR) are focused on several key areas to enhance the capabilities and effectiveness of these systems. Below are four directions for the development of these UAV detection and classification technologies.

1. *Advanced Machine Learning Algorithms*. The future of UAV detection systems lies in the implementation of advanced deep learning algorithms. These algorithms can be trained on extensive data sets encompassing a wide range of UAV signatures, allowing the systems to accurately distinguish drones from other flying objects, such as birds or aircraft, as well as effectively filter out background noise. By leveraging the power of deep learning, these systems can achieve significantly improved accuracy and efficiency in drone

identification, paving the way for more reliable and robust UAV detection [84].

2. *Sensor Fusion Technologies.* The integration of data from various optoelectronic sensors, including video, infrared, and LiDAR, can provide a comprehensive and multifaceted understanding of the UAV's environment. Sensor fusion enables UAV detection under a wide range of environmental conditions, such as low visibility due to night, fog, or cluttered backgrounds. By leveraging the unique strengths of each sensor type, these systems can achieve more accurate and reliable detection capabilities. Infrared sensors can detect thermal signatures, LiDAR can provide precise distance measurements, and video cameras can capture detailed visual information, all of which work in concert to enhance the overall performance of the UAV detection system [85,86].
3. *Self-learning Systems.* Future UAV detection systems will become increasingly autonomous, with the ability to learn from new data and continuously improve their detection and classification capabilities over time. This will involve the use of adaptive algorithms that can be updated based on new UAV detection scenarios, allowing the systems to adapt and evolve to address emerging challenges and threats. This self-learning capacity will enable these systems to stay ahead of the curve, maintaining their effectiveness in the face of changing UAV technologies and operational environments.
4. *Scalable Architectures.* As the complexity and scale of UAV detection challenges grow, the need for scalable architectures becomes paramount. Future systems will be designed with scalability in mind, allowing them to efficiently handle increasing data volumes, support larger coverage areas, and accommodate a rising number of drones and other aerial objects. This scalability will ensure that these detection systems can keep pace with the rapidly evolving UAV landscape, maintaining their effectiveness and reliability as the scope and demands of UAV monitoring and management expand.

By focusing on these key areas of development, future UAV detection and classification systems will become increasingly sophisticated, adaptable, and efficient, empowering stakeholders to effectively address the growing challenges posed by the proliferation of drones in various domains, from security and public safety to airspace management and environmental monitoring.

2.4. UAV detection and classification technologies based on acoustic sensors

2.4.1. Description of UAV detection and classification technologies based on acoustic sensors

Acoustic systems for detecting and classifying UAVs are divided according to the principle of operation into passive, active and combined (Fig. 4).

Passive acoustic systems use microphones to detect the sound produced by the UAV's engine. These systems can be useful for detecting UAVs over long distances, but they cannot identify the type or model of the UAV. Active acoustic systems use transmitters to emit sound waves that bounce off the UAV and return back. These systems can detect the type and model of UAV, but they have a limited range. Combination systems combine passive and active acoustic systems to provide both detection and recognition of UAVs. These systems typically have a long range and can identify the type and model of UAV. It is important to note that the effectiveness of these systems can depend on many factors, including environmental noise, weather conditions and the characteristics of the UAV itself. Analyzing algorithms for detecting and classifying UAVs as targets based on acoustic sensors, we can identify a number of technologies that provide high performance in accordance with the criteria of precision and range:

- Deep Learning using transformer-based models [49];
- Deep Learning based on the analysis of acoustic signatures [42,-44, 46];
- Machine learning and human performance [47];
- Machine Learning [45,48];

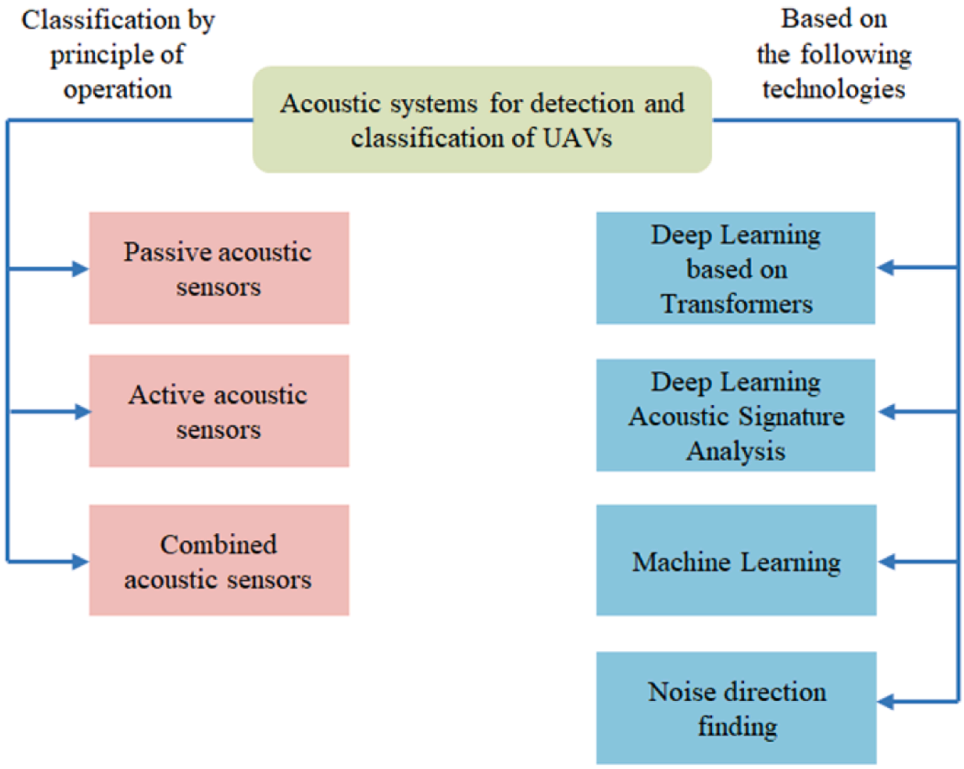


Fig. 4. Diagram of acoustic systems for detecting and classifying UAVs.

- Noise direction finding (sound intensity analysis, spectral analysis and direction finding) [41].

The research conducted by the authors in [44] focused on developing UAV detection and identification system using acoustic signatures and deep learning techniques. This paper presents an innovative solution for automatic detection and identification of UAVs based on their acoustic characteristics.

The operating principle of the system can be divided into four stages:

1. UAV detection. The system first detects the presence of a UAV in a certain area using acoustic sensors.
2. UAV identification. The system analyzes the characteristics of the UAV, such as its type or model, to determine whether the object is authorized or unauthorized.
3. UAV localization and tracking. The system determines the location of the drone and tracks its movement.
4. Obstructing the UAV mission. In the final stage, the system takes measures to interfere with the UAV mission using various methods such as shooting at the drone, using networks, using a laser beam, or interfering with the communication between the controller and the UAV to land it safely.

The article [49] presents an innovative approach that allows not only to detect a UAV, but also to recognize possible anomalies in its operation. The principle of operation is to use acoustic data collected using a microphone mounted on the UAV. This data is then put through an analysis process using DNN, including transformer and CNN models. Table 4 shows the performance indicators of modern acoustic systems for detecting and classifying UAVs. To evaluate performance, the authors used the following performance metrics: larger area under the ROC curve (AUC), Accuracy, Precision, Recall, F1.

2.4.2. Future directions for research and improvement of UAV detection and classification technologies based on acoustic sensors

This section discusses four promising directions for the development of acoustic hardware-based technologies for detection and classification of unmanned aerial vehicles (UAVs). These innovative approaches have the potential to revolutionize UAV surveillance and detection.

Table 4
Performance of acoustic UAV detection and classification systems.

Link	Technology	Performance
[43]	LD	AUC at 500 m: 63.25 %
	MLP	AUC at 500 m: 59.32 %
	SVM	AUC at 500 m: 65.52 %
	RF	AUC at 500 m: 51.01 %
	YAMNet	AUC at 500 m: 71.23 %
[44]	RNN	Accuracy: 75 %
	CNN	Accuracy: 96.38 %
	CRNN	Accuracy: 94.72 %
[45]	Medium Gaussian SVM	Accuracy: 99.9 %
		Precision: 100 %
		Recall: 99.8 %
[46]	Concurrent Neural Networks with Wigner-Ville	Precision: 91 %
	Spectrogram class	Recall: 90 %
	Concurrent Neural Networks with MFCC	F1: 90 %
	Concurrent Neural Networks with MIF	Precision: 86 %
		Recall: 86 %
		F1: 86 %
		Precision: 88 %
		Recall: 88 %
		F1: 88 %
[47]	Machine learning and Human Performance	92.47 %
[48]	SVM	Accuracy: 100 %;
	Gaussian Naive Bayes	Accuracy: 95.9 %;
	KNN	Accuracy: 98.9 %;
	NN	Accuracy: 99.7 %;

1. *Using advanced acoustic augmentation.* Recent studies have aimed to improve the robustness and applicability of acoustic classifiers by using advanced machine learning techniques and simple data augmentation methods. Innovative techniques such as pitch lift, time delays, harmonic changes, and ambient noise integration have been shown to significantly improve the performance of online acoustic classifiers, making them more robust to environmental challenges [87].
2. *Investigating the influence of range and environment.* The performance of UAV acoustic detection depends to varying degrees on the distance between the sensor and the target, as well as the level of ambient noise in the environment. Research shows that training machine learning models with attenuated acoustic signals can extend the detection range, enabling more reliable and long-range monitoring. For example, using a deep neural network, researchers have realized UAV detection at ranges of up to 500 m, providing the potential for acoustic detection in practical surveillance applications for the first time [43].
3. *Comprehensive Databases.* Developing large, high-quality databases containing a wide range of UAV acoustic signals is critical to determining detection accuracy. These comprehensive datasets quickly train modified machine learning models, enabling them to recognize different types of drones and their unique characteristics in different environments.
4. *Using DL algorithms.* Current research also includes developing adaptive and context-aware acoustic algorithms that can adjust their detection and classification strategies based on changing environmental conditions and operational phenomena. These intelligent systems can learn from past experiences, optimize their performance, and adapt to emerging threats, providing more reliable and versatile UAV monitoring capabilities in real-world applications [88,89].

Continued development of four promising research areas in acoustic-based UAV detection and classification technologies has the potential to significantly improve the efficiency, accuracy, and adaptability of UAV surveillance systems, ultimately enhancing public and national security in the face of the increasingly common drone threat.

2.5. UAV detection and classification technologies based on sensor fusion

2.5.1. Description of UAV detection and classification technologies based on sensor fusion

Detection and classification of UAVs using hybrid technologies Sensor fusion is the integration of the functionality of different types of sensors in order to improve system performance in terms of precision, range and probability of false alarms. Based on data analysis, Sensor Fusion systems are able to identify UAVs in relation to objects of another class (in particular birds), determine the type, its unique characteristics, current dynamic parameters (speed, direction, range, etc.). This technology is used for various purposes, including detection and tracking of UAVs, preventing unauthorized flights, ensuring airspace security and others.

As a result of a review of scientific articles from the Scopus and Web of Science databases not older than 2020, the following combinations of Sensor Fusion technologies were identified:

- acoustic and optical-electronic sensors [51,55–57];
- optical-electronic satellite sensors and radars [50,51,54,59,60];
- optical-electronic, acoustic sensors and radars [52,62];
- optical-electronic and RF-based sensors [55];
- optical-electronic, RF-based and acoustic sensors [53].
- RF-based and acoustic sensors [61].

In [56], the authors proposed a multi-sensor UAV detection system using advanced machine learning methods. The operating principle of this system is to combine data from various sensors for detection and

classification. The system operation algorithm is presented in the form of five stages:

1. Data collection. Various sensors such as an infrared camera, a video camera, audio sensors and a panoramic camera collect information about the surrounding environment.
2. Data processing. The obtained data is processed using machine learning methods to analyze and extract features characteristic of the UAV.
3. Data fusion. Data from various sensors is combined to create a comprehensive overview of the surrounding environment and detect potential UAVs.
4. Classification. Based on the extracted features and data from various sensors, the detected objects are classified as UAVs or other objects (for example, birds, airplanes).
5. Tracking. The system can also track the movement and trajectory of detected objects for further analysis and monitoring.

The results of the study [56] indicate the successful application of general machine learning methods to infrared sensor data, making them effective for UAV detection. The infrared detector achieves an F1-measure of 0.76 (76 %), which also confirms the good Precision and Recall of UAV detection and classification. This result is comparable to the performance of the video detector, which has an F1-measure of 0.78 (78 %) and the audio detector of 0.93 (93 %). Thus, the use of infrared sensors, audio sensors, video detectors (video surveillance cameras) in combination with machine learning methods can be considered an effective way to detect and classify UAVs, providing high performance according to accuracy criteria (F1-measure, Recall).

In article [55] the authors proposed a detection system based on artificial neural networks, where a DNN processes data from RF-based sensors, and a CNN processes images from a video detector. Features from both networks are combined and fed into the input of another DNN, which produces an assessment of the presence of a UAV. The accuracy of this technology was 75 %.

A data fusion strategy based on combining frames of optical-electronic surveillance equipment and radar signals to improve UAV detection was proposed by the authors [50]. This Sensor Fusion system has two levels:

1. Data layer. At this level, the information received from the optical-electronic sensor (video detector) and radar is merged to determine the coordinates and position of the UAV. Optical-electronic data is used to extract visual characteristics of a target, while radar signals can help determine the distance and speed of an object.
2. Decision-making level. At this level, the unique characteristics of the UAV are merged to more accurately identify and classify the target. Information about the UAV visual characteristics and coordinates is combined to make a target identification decision.

Thus, the technology [50] consists of the joint use of data from computer vision and radar to determine the coordinates and unique characteristics of the UAV.

In [61], the authors presented a technology for fusion of RF and acoustic characteristics for UAV classification. They propose using both classical and deep machine learning methods, as well as combining RF and acoustic features to more accurately and efficiently classify drones. Their study used various neural network-based classifiers (DNN, CNN, LSTM, GRU) and the classical SVM method. The accuracy of this technology is about 91 % at a signal-to-noise ratio (SNR) of −10 dB using LSTM features. Its advantage is high noise immunity and significant improvement in accuracy in noisy environments with low signal-to-noise ratio. In addition, this technology outperforms existing drone classification methods, especially in low signal-to-noise ratio (−20 dB) environments.

In [62], the authors presented a sensor fusion strategy for non-cooperative detection and avoidance (SAA) for UAVs flying at low altitudes. This strategy integrates radar and optical-electronic sensor data at both the detection and tracking levels to benefit accuracy. The proposed strategy is called Fuse-Before-Track (FBT) through a two-step approach of using radar and visual information together to remove uninteresting echoes and ground clutter. Tracking is also accomplished by using radar measurements and combining visual detections to improve the accuracy of the solution. The relative positioning decision is made using differential carrier phase GNSS techniques. Thus, the improved layer fusion approach provides meter-level and meter-per-second level radar detection accuracy for range and speed, respectively.

2.5.2. *Future directions for research and improvement of UAV detection and classification technologies based on sensor fusion*

Future directions for UAV detection and classification systems based on hybrid sensor fusion (including electro-optical, radar, RF, and acoustic sensors) aim to improve their accuracy, reliability, and real-time capabilities. This multi-faceted approach offers a comprehensive solution to address the evolving challenges in UAV classification and detection. Below are four directions of research and development of sensor fusion UAV detection and classification system.

1. *Enhanced Sensor Fusion Algorithms.* Advanced algorithms for fusion of multi-sensor data are critical to improving the performance of UAV detection and classification systems. Techniques such as machine learning and deep learning will play an important role in integrating data from multiple sensor modalities, including electro-optical, radar, RF, and acoustic sensors. This integration will help improve the overall classification accuracy even in complex environments [52,63].
2. *Real-Time Data Processing and AI Integration.* With the rapid movement and proliferation of UAVs, real-time processing is of utmost importance. By leveraging the power of AI and machine learning models, Sensor Fusion systems will improve to process large volumes of sensor data in real-time, enabling faster and more accurate detection and classification. This is especially important for applications in densely populated areas or complex environments where fast decision-making is critical to respond to potential threats or unauthorized drone activity [90].
3. *Countermeasure Resilience.* Recognizing the evolving threat landscape, future UAV detection and classification systems will be designed to be resilient to a variety of countermeasures. This includes developing robust methods to mitigate the impact of jamming, spoofing, and other electronic warfare tactics that adversaries may use to disrupt or deceive detection systems. By incorporating countermeasure resilience, these systems will remain effective and reliable even in the face of modern and evolving threats.
4. *Privacy-Preserving Fusion methods.* Addressing privacy concerns by developing fusion methods that preserve privacy while maintaining high UAV detection accuracy. As the use of UAVs becomes more prevalent, there is a growing need to balance effective surveillance and detection capabilities with protecting the privacy rights of individuals. Developing fusion methods that can accurately detect and classify UAVs without compromising personal privacy is a major challenge that researchers and developers must address [91,92].

The integration of advanced sensor fusion algorithms, real-time AI processing, and robust multi-sensor networks will shape the future of UAV detection and classification systems. These technological advances will significantly enhance the ability to detect, classify, and counter UAV threats in an increasingly complex and contested environment. As the scope of aerial threats continues to evolve, the development of advanced UAV detection and classification systems remains a critical priority for both public and private sector stakeholders.

3. Use of UAV detection and classification technologies in modern anti-drone systems

3.1. Description of methods of suppressing and destroying UAVs

Currently, many companies are designing Anti-Drone devices and systems that are based on the optical-electronic, acoustic, RF and radar technologies for detecting and classifying UAVs discussed above. These software and hardware systems combine several technologies, corresponding to the well-known Sensor Fusion principle. The optical-electronic components of Anti-Drone systems use cameras and infrared sensors for visual detection. The radar unit is aimed at emitting electromagnetic waves, which are reflected from objects and return back to the radar, allowing you to determine the distance to the object, its speed and direction. The radio frequency detection channel of Anti-Drone systems monitors the radio frequency spectrum for the presence of signals transmitted by drones. Acoustic sensors in the systems detect drones by the sound they make. An indispensable component of the Anti-Drone systems software package is artificial intelligence. Artificial intelligence is represented by neural networks, machine learning and deep learning algorithms that perform classification tasks, UAV recognition, data analysis from different sensor channels, and decision making. In addition to detection and classification tasks, Anti-Drone systems are capable of eliminating UAVs.

Common methods of suppressing and destroying UAVs:

- Electronic jamming - this method includes cyber-attacks, GPS substitution, interception of control and jamming, which contributes to the loss of communication between the drone and the operator or to his disorientation;
- Physical impact - interception of a UAV by a fighter drone, the use of nets and projectiles [63];
- Powerful microwave radiation - damage to UAV electronics by powerful microwave radiation, which leads to failure of electronic components [63];
- Laser – the use of a laser as a weapon [64] or as a countermeasure to the optical sensors of UAVs [65].

The work [66] presents destructive and non-destructive methods of UAV cyberattacks. Non-destructive cyber-attack methods include four approaches. The first approach is information leakage, which can lead to the disclosure of protected information. An example would be obtaining information about a UAV's mission or data to look up a Wi-Fi password. The second approach is integrity violation, where UAV data may be destroyed, corrupted, or altered. This type of attack can only be detected after it has occurred. The third approach is denial of service (DoS), which makes it impossible to use the UAV system. The fourth approach is illegal use of information aimed at accessing non-public parts of the system or using certain services without permission. For example, using a stolen password to decrypt an intercepted communication or seize control. These cyberattack techniques can result in obtaining sensitive information, altering data, or disrupting a system without causing physical damage. Destructive methods of cyber-attacks involve a direct impact on the object, which ultimately leads to irreversible physical damage to the UAV hardware complex, due to vulnerabilities at low levels of the OSI model.

3.2. Anti-drone systems review using modern UAV detection and classification systems

Based on quality parameters, such as detection efficiency, identification accuracy, reliability, speed, information security, adaptability and flexibility, the following Anti-Drone systems can be distinguished:

- DedroneRapidResponse [76];
- IXI Technology Drone Killer [71];
- SkyWall Patrol [67];
- Liteye AUDS [74];
- Kaspersky Antidrone [77];
- MSI-Defence Systems Terrahawk Paladin [78];
- Elbit Systems ReDrone [79].

DedroneRapidResponse provides a mobile solution for detecting, tracking and identifying UAVs based on artificial intelligence. This software and hardware complex uses cloud software to accurately determine the location of the drone even when the target takes off, which gives security teams and special units a significant gain in time. DedroneRapidResponse does not include built-in tools for neutralizing UAVs. However, it can be integrated with other systems to provide a full range of protection. Featuring a portable drone detection subsystem, including radars, RF sensors and an optical-electronic recognition channel, DedroneRapidResponse is capable of detecting and identifying UAVs at a distance of >5 km.

The IXI Technology DroneKiller Anti-Drone system is a portable device that uses SDR technology to detect and eliminate UAVs. This device blocks GPS signals, forcing targets to descend or return to their take-off point. DroneKiller is also capable of disabling UAVs on seven frequency bands at a distance of up to 1000 m. Due to its portability and lightness, this Anti-Drone device can be deployed inside light vehicles, as well as used by first response teams in mobile units, strike groups, and checkpoints.

The Liteye Anti-UAV Defense System (AUDS) is a strategic counter-UAV system designed to detect, track and neutralize them. AUDS integrates radar scanning for target acquisition, electro-optical tracking and classification, and directional radio frequency jamming technology. The system is used to protect critical infrastructure in dense urban areas. The installation is also deployed on mobile and robotic vehicles to support a range of missions such as air and ground base defense, convoy protection, offensive electronic attack and non-military missions such as wildfire response and event security.

The SkyWall Patrol Anti-Drone is a portable system that provides the operator with the ability to physically capture the drone in a specially designed network. The device uses a built-in SmartScope optical-electronic sight for detection and targeting of UAVs. The sight automatically compensates for the UAV's speed and distance, allowing the operator to accurately target it. After identifying a target, SkyWall Patrol uses compressed air to launch a projectile towards the UAV. The projectile splits into two as it approaches the target and deploys a net to capture it. Some projectiles contain a parachute that controls the descent of the captured UAV, minimizing the risk of collateral damage and keeping the device intact for later analysis.

SkyWall Patrol is not only used as a standalone anti-UAV solution, it also integrates with the wider security system using the SkyLink module to create a highly effective countermeasures package. A single SkyWall Patrol system can protect a specific area, or multiple systems can be deployed from mobile platforms to protect a large strategic location.

Kaspersky Anti-Drone is a software and hardware system that uses artificial intelligence and neural networks to detect, classify and track UAVs of various types and classes. This system uses a primary detection module, which may be a device capable of scanning the airspace above the protected area. Such a device can be a lidar, radio frequency sensor, radar, or PTZ video surveillance camera. Artificial intelligence-based algorithms are used to recognize and classify UAVs. This allows for high speed data processing from hardware sensors of various types and provides comprehensive analytics for UAVs in a single interface. Kaspersky Anti-Drone also uses an optical detection module that classifies the drone at any time of the day thanks to PTZ cameras. After detecting and classifying the UAV, the system tracks the target, waiting for a command to be sent to the jammer.

Table 5 provides information on known models of Anti-Drone systems, the main characteristics and technologies used for detecting, classifying and eliminating UAVs.

Table 5
Performance of acoustic UAV detection and classification systems.

System description	Characteristics (range, ranges, accuracy)	Detection and classification technologies	UAV elimination technologies
SkyWall Patrol [67]	Maximum Range: 100 m (330 feet)	Optical-electronic	Physical elimination
DroneShield DroneGun Tactical [68]	Maximum Range: 2000 m	RF-based	Electronic jamming
Aaronia Drone Detection System [69]	Maximum Detection Range: Up to 50 kms. Frequency Range: 20 MHz to 8 GHz. Tracking Accuracy (line of sight): 4 to 6°.	RF-based	Electronic jamming
Fortem DroneHunter [70]	Detection Range: 500 m. Azimuth and Elevation Accuracy: ±2°	Radar	Physical elimination
IXI Technology Drone Killer [71]	Effective Range: Up to 1000 m or approximately 0.62 miles	RF-based	Electronic jamming
DJI Aero Scope [72]	Reliable Detection Range: Up to 16 km. Maximum Detection Range: Up to 32–48 km. Maximum Monitoring Range: Up to 50 km.	RF-based	–
Anduril Lattice Counter Drone System [73]	Maximum detection range for UAV: from 5 to 20 km (depends on UAV size)	Radar, optical-electronic	Physical elimination (shot down by another UAV)
Liteye AUDS [74]	Detection Range: Up to 10 km. Effective Range for Micro UAVs: Up to 2 km.	Radar, optical-electronic	Electronic jamming
ELI-4030 Drone Guard [75]	Detection Range: Up to 4.5 km. DOA Accuracy: ±2°. Frequency Coverage: 400 to 6000 MHz.	Radar, RF-based	Electronic jamming
DedroneRapidResponse [76]	RF Range: Up to 5 km. PTZ Range: Up to 1 km. Radar Range: Up to 1 km.	Radar, optical-electronic, RF-based	–
Kaspersky Anti-drone [77]	Detection Range: Up to 5 km. RF Range: Up to 1 km. Average Classification Accuracy: 97 %.	Radar, optical-electronic, RF-based	–
MSI-Defence Systems Terrahawk Paladin [78]	Elimination range of air targets: up to 2 km.	Radar, optical-electronic	Physical elimination (use of automatic artillery mount)
Elbit Systems ReDrone [79]	Range: from 2 km or more; 360° coverage	Radar, optical-electronic, acoustic, RF-based	Electronic jamming

The MSI-Defence Systems Terrahawk Paladin [78] system is a counter-UAV system that provides target elimination in the short range of air defense. This Anti-Drone consists of three main components: a radar station, a digital fire control system and an automatic artillery mount. The system uses FIELD and SKY radars, as well as AI technologies for ballistic calculations. An optical-electronic unit with daytime and thermal imaging cameras helps identify potential threats during the day, in adverse conditions or at night. The Mk 44 Bushmaster II 30 mm artillery mount is used to destroy targets. When using ammunition with software detonation, the range of destruction of air targets can reach up to 2 km.

The Elbit Systems ReDrone [79] system is an innovative solution for detecting and blocking threats associated with the use of UAVs. It is designed to ensure the security of military, police, civilian facilities, as well as at state borders, airports, seaports, strategic sites, public events, landmarks, prisons, military bases and convoys. ReDrone uses a unique set of countermeasures that detect, identify, classify, locate, track, neutralize, manipulate and destroy multiple threats simultaneously. Various detection technologies are used for this, including SIGINT, which detects all types of commercial drones, identifies them and alerts the operator. 2D or 3D radars are also used for active detection and positioning. Once a target is detected, ReDrone blocks all radio and GNSS signals, disrupts the drone's communication with the operator and sends it off course, preventing the possibility of an attack.

Thus, the future of modern Anti-Drone systems is determined in the advancement of defense technologies, the application of artificial intelligence and neural networks, and integration with existing security systems. These systems are being developed to detect, classify, and mitigate UAVs using a variety of methods, including camera systems, drone detection radar, net guns, and cyber takeover systems. The use of Sensor data fusion, such as RF-based analyzers, acoustic sensors, optical sensors, and radar, is also a significant area of focus. As the technology evolves, these systems are expected to become more efficient and accurate, providing a robust solution to the growing threat posed by UAVs.

4. Conclusion

In conclusion, the field of UAV detection and classification is advancing rapidly, driven by the integration of diverse technologies such as radar, RF sensors, acoustic detectors, and optical imaging systems. The incorporation of machine learning and artificial intelligence plays a pivotal role in refining these technologies, enabling more accurate and reliable systems. Sensor fusion technology, which combines data from multiple sources, exemplifies the trend towards holistic detection approaches that can adapt to the varied challenges presented by UAV monitoring. Continued innovation is essential to address the evolving complexities of UAV technologies and their applications. By improving the sensitivity and specificity of detection methods and harnessing the power of AI for real-time analysis and decision-making, future systems will not only enhance airspace security but also facilitate the safe integration of UAVs into civil and commercial environments. This comprehensive progress in UAV detection and classification technologies holds significant promise for a wide range of applications, making ongoing research and development a crucial investment for both safety and technological advancement.

[23,58].

CRediT authorship contribution statement

Vladislav Semenyuk: Software, Resources, Data curation, Conceptualization. **Ildar Kurmashev:** Supervision, Project administration, Funding acquisition, Conceptualization. **Alberto Lupidi:** Visualization, Software, Methodology. **Dmitriy Alyoshin:** Writing – review & editing, Writing – original draft, Conceptualization. **Liliya Kurmasheva:** Writing – review & editing, Methodology, Formal analysis. **Alessandro Cantelli-Forti:** Writing – review & editing, Writing – original draft,

Supervision, Project administration.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Ildar Kurmashev reports financial support was provided by Manash Kozybayev North Kazakhstan University. This research is funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No AP19679009) If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research is funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No AP19679009).

Data availability

Data will be made available on request.

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