remote sensing

Review

A Comprehensive Survey of Unmanned Aerial Vehicles Detection and Classification Using Machine Learning Approach: Challenges, Solutions, and Future Directions

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Abstract: Autonomous unmanned aerial vehicles (UAVs) have several advantages in various fields, including disaster relief, aerial photography and videography, mapping and surveying, farming, as well as defense and public usage. However, there is a growing probability that UAVs could be misused to breach vital locations such as airports and power plants without authorization, endangering public safety. Because of this, it is critical to accurately and swiftly identify different types of UAVs to prevent their misuse and prevent security issues arising from unauthorized access. In recent years, machine learning (ML) algorithms have shown promise in automatically addressing the aforementioned concerns and providing accurate detection and classification of UAVs across a broad range. This technology is considered highly promising for UAV systems. In this survey, we describe the recent use of various UAV detection and classification technologies based on ML and deep learning (DL) algorithms. Four types of UAV detection and classification technologies based on ML are considered in this survey: radio frequency-based UAV detection, visual data (images/video)-based UAV detection, acoustic/sound-based UAV detection, and radar-based UAV detection. Additionally, this survey report explores hybrid sensor- and reinforcement learning-based UAV detection and classification using ML. Furthermore, we consider method challenges, solutions, and possible future research directions for ML-based UAV detection. Moreover, the dataset information of UAV detection and classification technologies is extensively explored. This investigation holds potential as a study for current UAV detection and classification research, particularly for ML- and DL-based UAV detection approaches.

Keywords: UAV detection and classification; machine learning-based detection; deep learning-based detection

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1. Introduction

Unmanned aerial vehicles (UAVs), sometimes referred to as drones, have garnered significant attention in recent years. Through the use of a remote controller, UAVs can be operated without a pilot present from a distance of miles. UAVs are utilized in combat, surveillance, airstrikes, investigations, and various other operations [1]. In addition, UAVs are useful instruments in various industries, and they are currently being used for a wide range of purposes. For instance, authorities utilize UAVs in disaster prevention [2], remote sensing [3], environmental monitoring [1], and so on. They are also employed by companies like Amazon, UPS Inc., and others for product delivery [4]. Additionally, UAVs play a crucial role in agriculture, aiding in crop observation [5] and the application of pesticides and fertilizers [3]. Furthermore, emergency personnel, along with emergency medical services and enthusiasts, utilize UAVs for tasks such as rescue operations, medical assistance, and recreational imaging [1].

However, instead of the emerging applications of UAVs, in recent years, challenges regarding privacy and safety have been raised by the use of UAV systems [6]. The introduction of recreational UAVs into national airspace has sparked worries about unqualified and unlicensed pilots entering forbidden areas and interfering with aircraft operations. Inadequate rules when buying UAVs may be part of the problem. For instance, a national defense aircraft was struck by a private UAV just over two years ago [7]. The use of UAVs for unlawful monitoring and terrorist attacks are the most worrisome issues [8]. To prevent the aforementioned incidents, an anti-UAV technology that can identify, classify, and neutralize unlicensed UAVs collecting data using various sensors is needed [9]. Recently, for the classification and detection of UAVs, numerous studies have investigated ways to identify UAVs utilizing a range of technological advances, such as thermal imaging, audio, video, radio frequency (RF), and radar. Using these technologies, there are many traditional methods to identify or detect unwanted UAVs, but most of the methods have failed to provide an adequate prevention rate during the detection of UAVs.

In recent years, the fields of object detection [10], image segmentation [11,12], and disease recognition [13] have undergone a dramatic transformation due to the emerging advantages of machine learning (ML) and deep learning (DL) approaches [14]. Consequently, UAV detection [15] has gained popularity in the scientific community following the advent of DL techniques. The emerging advantages of ML and DL for UAV detection include data efficiency, decreased computational intensity, automatic feature learning, high-accuracy UAV classification, and end-to-end learning capabilities. On the other hand, there are some disadvantages of ML and DL, such as limited performance on more intricate UAV detection tasks and DL models requiring large amounts of labeled data for training, which may be a limitation in scenarios where obtaining labeled data is challenging or expensive. In [16], the authors proposed a deep neural network (DNN) that classifies multirotor UAVs using acoustic signature inputs. The primary focus of this research lies in ML-based detection and classification methods. ML has demonstrated significant benefits in object detection and classification across a range of domains due to its capacity to identify patterns without the need for human intervention. Reducing the reliance on human intervention is desirable for various reasons, including human limitations in identifying tiny or distant objects and the potential for concentration deficits brought on by boredom or exhaustion. Instead, ML can recognize patterns using paradigms that are entirely imperceptible to the human eye. These include transmissions that are not detectable by human sensory systems, such as RF, optical, and audio messages.

Given the aforementioned advances in object detection and classification using ML, in this review, UAV detection and classification undergo extensive study regarding challenges, solutions, and future research directions using ML and UAV detection by highlighting the advantages and limitations of methods, and the improvement pathway is described in detail. After that, a thorough critical analysis of the state of the art is presented. In addition, an extensive review of dataset information is provided for UAV detection classification technologies. In addition, reinforcement learning-based UAV detection and classification with a detailed research direction are presented. Additionally, a review of hybrid sensor-based UAV detection strategies provides detailed datasets and a clear research direction. The most similar work to our proposed survey is in [17], where the authors present a report with various literature references without in-depth analysis of each of the methods. In our proposed survey, we include a detailed discussion regarding state-of-the-art literature, and the important key difference from [17] is that our report provides detailed dataset information for all the UAV detection and classification technology using ML and DL algorithms, which will be helpful for both advanced and beginner researchers in the UAV detection field. In addition, RL-based UAV detection and classification with a detailed research direction are presented in the proposed survey report.

In recent years, many surveys have been conducted on UAV systems, and most works focus on object detection and classification using UAV-assisted images in the applications of agricultural crop classification [18,19], vehicle detection [20,21], identification of plant and crop diseases [22], forestry [23], crop disease detection [24], and so on. In contrast, this survey report is focused on UAV or drone detection using five different technologies based on ML and DL algorithms. A few survey reports have been published for UAV detection and classification in the last few years, and the key differences between those reports and our survey report are mentioned in Table 1.

Table 1. Contribution of this survey with other works for ML-based UAV classification and detection.

References	Contribution
[17]	Review on drone detection and classification using ML up to the year 2019. The study provides limited insights into the performance of original detection approaches and references.
[25]	Review on UAV-based communications using ML, focusing on resource management, channel modeling, location, and security up to the year 2019.
[26]	Review of the technical classification and implementation methods of UAV detection and tracking in urban IoT environment and provided a limited number of references covering up to the year 2023.
[27]	Survey on DL-based UAV detection, with a focus on radar technologies up to the year 2021.
[28]	Survey on ML-based radar sensor networks for detecting and classifying multirotor UAVs up to the year 2020.
[29]	Survey on the detection of unauthorized UAVs up to the year 2022. However, the study does not cover specific ML types and state-of-the-art detection approaches.
[30]	Review of drone detection strategies that emphasize the use of DL with multisensor data up to the year 2019.
[31]	Review of drone identification, neutralization, and detection, with less emphasis on detection methods. The study primarily focuses on system design from the regulatory viewpoint, excluding state-of-the-art detection techniques and references covered up to the year 2021.
This survey	Review on UAV detection and classification that provides an extensive survey including suggested challenges, solutions, and future research directions using ML (e.g., addressed technologies encompass radar, visual, acoustic, and radio frequency sensing systems) up to the year of 2023. This study covers UAV detection by highlighting the advantages and limitations of methods and the improvement pathway. After that, a thorough critical analysis of the state of the art is presented (e.g., including different methodologies for different technologies, performance accuracy with different matrix indexes, and machine learning model types). In addition, an extensive review of dataset information is provided for UAV detection and classification technologies (e.g., publicly available and own experimental datasets with details such as classes, training, testing ratios, and used experimental drones). In addition, reinforcement learning (RL)-based UAV detection and classification with detailed research direction are presented. Moreover, a review of hybrid sensor-based UAV detection strategies provides detailed datasets and research direction.

In the remaining sections of this survey, classification of four UAV detection techniques with ML is described in Section 2. Figure 1 illustrates the organization of this paper in detail. Finally, the conclusion and discussion are presented in Section 3.

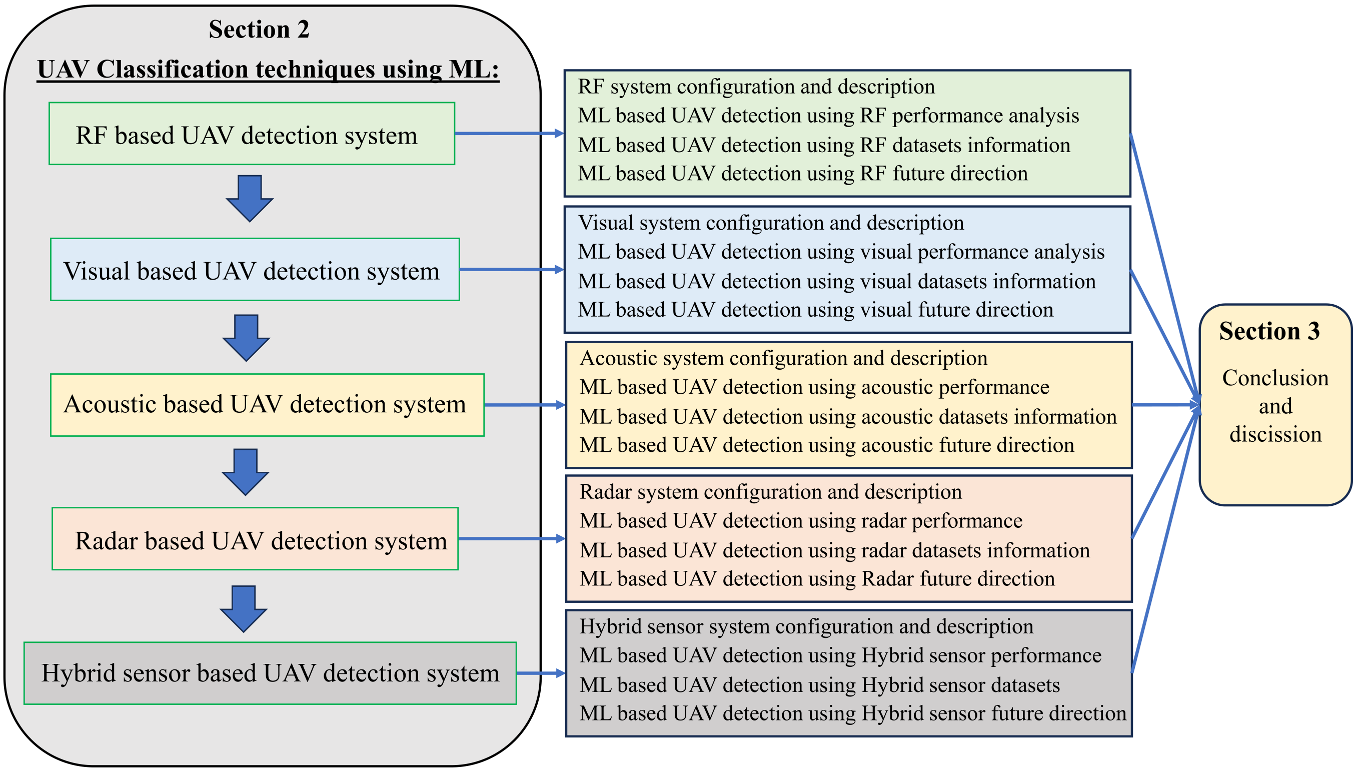

Figure 1. The overview of the organization of this paper.

2. UAV Classification Categories

In this section, the different UAV detection and classification categories based on ML are described. Figure 2 shows the graphical demonstration of different UAV classification and detection categories, along with their corresponding advantages and disadvantages. The detection technologies for UAVs are classified into four groups: (1) RF-based detection, (2) visual data-based detection, (3) acoustic signal-based detection, and (4) radar-based detection. In addition, the hybrid sensor-based UAV detection and classification method is described at the end of this section. Each of the categories is described in the following section.

2.1. UAV Classification Based on ML Using RF Analysis

RF signals are captured and examined using RF-based devices in order to identify and recognize threats. The benefits of the RF-based detection method are that it operates day or night and in any kind of weather. Thus, compared with other current technologies, RF-based monitoring techniques have recently shown higher potential for the UAV communication system. In order to manage and operate the UAV utilizing RF signals, most UAVs are equipped with an onboard transmitter for data transfer.

UAVs can be detected and located from a considerable distance using RF information. To improve the challenges of UAV detection and classification rates using RF signals, the ML-based algorithm has shown excellent performance. The overview of the RF-based UAV detection and classification operation is illustrated in Figure 3. In addition, a summary of recent related research on RF-based methods using ML for UAV detection and classification is shown in Table 2. Furthermore, the dataset information of the current research on RF-based methods using ML for UAV detection and classification is shown in Table 3.

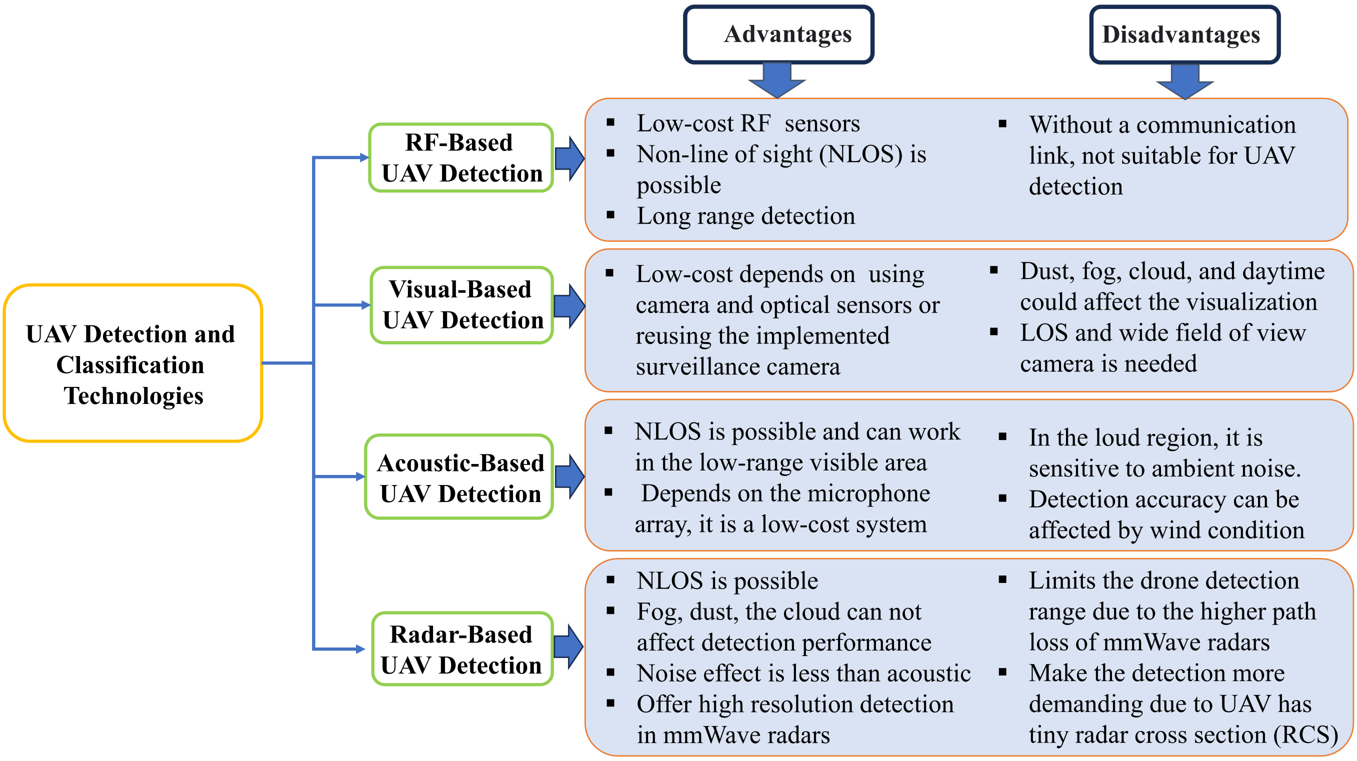

Figure 2. The different categories of UAV classification and detection technologies and their corresponding advantages and disadvantages.

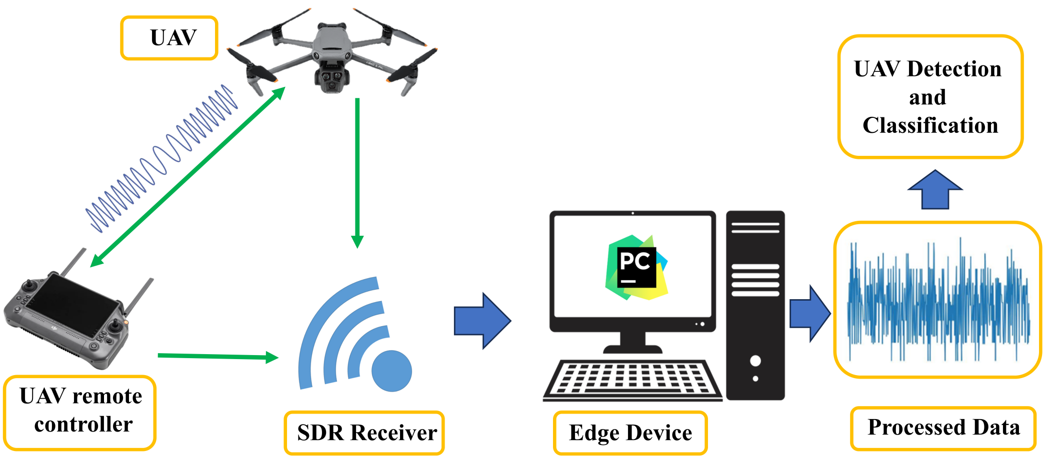

Figure 3. The detection and classification mechanism of UAV based on RF signal analysis.

Table 2. Comparison summary of ML-based UAV classification and detection using RF technology.

Reference	Detection Target	Machine Learning Method	Performance	Model Types [1]
[32]	UAV detection using RF	NN, ResNet50	Accuracy: 95%	SL, DTL
[33]	UAV detection using RF	Extreme Gradient Boosting (XG-Boost)	Accuracy: 99.6%, F-1 score: 100%	SL
[34]	UAV detection and classification	CNN, Logistic regression (LR), KNN	Accuracy: 100% for 2 classes and 98.0% for 10 classes	SL

Table 2. *Cont.*

Reference	Detection Target	Machine Learning Method	Performance	Model Types [1]
[35]	UAV detection using RF	CNN	Accuracy: 92.5%, F1-score: 93.5%	SL
[36]	UAV detection using RF	Bayesian, SVM, MLP	Accuracy: 99%, Recall: 99.5%	SL
[37]	UAV detection using RF	ANN	Accuracy: 82% within 3 km distance	SL
[38]	UAV classification from raw RF fingerprints	Markov-based naïve Bayes detection, KNN, DA, SVM, NN	Accuracy: 95%, 96.84%, 88.15%, 58.49% with different models	SL
[39]	UAV controller detection from transmitted control RF	CNN	N/A	SL
[40]	Detection of UAV type and flight mode from raw RF signals	DNN	Accuracy: 99.7% for 2, 84.5% for 4, and 46.8% for 10 classes, F1-score: 99.5% for 2, 78.8% for 4, and 43.0% for 10 classes	SL
[41]	UAV detection using RF	End-to-End CNN Model	Accuracy: 97.53%, Precision: 98.06%, Recall: 98.00%, and F1-score: 98.00%	SL
[42]	UAV detection using RF	XGBoost, AdaBoost, decision tree, random forest, KNN, and MLP	Accuracy: 100%, 99.6%, and 99.3% for 2, 4, and 10 classes, F1-score: 100%, 99.6%, and 99.3% for 2, 4, and 10 classes	SL
[43]	Swarm of UAV detection using RF	PCA, ICA, UMAP, t-SNE K-means, mean shift, and X-means	Accuracy: 99% for the VRF dataset, 100% for the XBee dataset, and 95% for Matrice dataset	USL
[44]	UAV detection using RF	YOLO-lite, Tiny-YOLOv2, DRNN	Accuracy: YOLO-lite, Tiny-YOLOv2, and DRNN were 97%, 98%, and 99%	SL
[45]	UAV detection using RF	Residual CNN	Accuracy: 99%, F1-score: 97.3 to 99.7%	SL
[46]	UAV detection using RF	Hierarchical ML (KNN and XGBoost)	Accuracy: 99.20%, Precision: 99.11%, F1-score: 99.10%	SL
[47]	UAV detection using RF	CNN	Accuracy: 99.80%, Precision: 99.85%, Recall: 99.55%, F1-score: 99.70%	SL
[48]	UAV detection using RF	KNN	Accuracy: 98.13%	SL
[49]	UAV detection using RF	FNN, CNN	Accuracy: 92.02%, Precision: 94.33%, Recall: 94.13%, F1-score: 94.14%	SL
[50]	UAV detection using RF	Hierarchical ML (CNN, SVM)	Accuracy: 99%	SL
[51]	UAV detection using RF signatures	Autoencoder (AE), LSTM, CNN, and CNN-LSTM hybrid model	Accuracy: 88.02%, Recall: 99.01%, F1-score: 85.37%	SL
[52]	UAV detection using RF signatures	Power spectrum density (PSD) with DNN model called PSD	Accuracy: 89%	SL
[53]	UAV detection using RF	Multiscale-1D CNN	Accuracy: 99.89% for 2 class, 98.56% for 4 class, 87.67% for 10 class; F-1 score: 99.96% for 2 class, 98.87% for 4 class, 86.82% for 10 class	SL
[54]	UAV detection using RF	MLP-based Model-URANUS	Accuracy: 90.0%	SL
[55]	UAV detection using RF	Hybrid (1DCNN + XGBoost classifier)	Accuracy: 100% for 2 class, 99.82% for 4 class, 99.51% for 10 class	SL
[56]	UAV detection using RF	Residual network-based autoencoder (DE-FEND)	Accuracy: 100%	SSL, USL

[1] SL = supervised learning, USL = unsupervised learning, DTL = deep transfer learning, SSL = semi-supervised learning.

Table 3. Datasets information of UAV classification and detection using RF technology.

Reference	Datasets Information
[32]	Used own datasets including 5 drones Parrot ANAFI, FIMI X8SE, DJI Phantom 4 Pro V2.0, DJI Mavic Air, and DJI Mavic Mini 2 collected from the hardware configuration of operating frequency, sampling rate, center frequency, and receiving bandwidth of USRP X310 set to 100 Msa/s, 5785 MHz, and 100 MHz. The background data undergo random spectral shifting range of $[-40, 40]$ MHz in every training batch. Training sample SNR or SINR was adjusted by varying AWGN power and weight coefficient.
[33]	Used the datasets called DroneRF datasets (composed of227 recorded segments collected from 3 different drones, size of datasets 3.75 GB) [57].
[34]	BladeRF software (https://www.nuand.com/bladerf-1/, accessed on 26 January 2024) defined radio (SDR) was used to collect samples from 3 types of UAV and background activities, Each dataset entry contains $12,000,000$ samples.
[35]	DroneRF datasets (composed of 227 recorded segments collected from 3 different drones, size of datasets 3.75 GB) [57].
[36]	Airborne datasets were collected by measurement device underneath a commercial UAV; ground and airborne sample numbers are 1535 and 5922.
[37]	Used indoor datasets of 1 to 500, 501 to 1000, and 1001 to 1500 correspond to the distance of 5 m, 10 m, and 15 m and outdoor datasets of 1 to 500, 501 to 1000, 1001 to 1500, 1501 to 2000, 2001 to 2500, 2501 to 3000, 3001 to 3500, 3501 to 4000, and 4001 to 4500 corresponding to a distance of 0.005 km, 0.01 km, 0.02 km, 0.5 km, 1 km, 1.5 km, 2 km, 2.5 km, and 3 km between Rx and u, respectively. It belongs to the UAV class, non-UAV class.
[38]	Used own datasets, which were collected indoors from 14 micro-UAV controllers operating at 2.4 GHz in near-field mode [58].
[40]	Used own datasets containing Parrot Bebop, Parrot AR Drone, DJI Phantom 3 drones with Wi-Fi signals and flight modes using hardware [59] with totals samples 3720×10^6.
[41]	Used publicly available CardRF datasets [60], which contained UAS, Wi-Fi, and Bluetooth with no. of signals 3395, 700, and 1750, respectively.
[42]	DroneRF datasets (composed of 227 recorded segments collected from 3 different drones, size of datasets 3.75 GB). [57]
[43]	Used various RF Sources (VRF Dataset) from [57,58,61], which include four different types of drones and two other RF sources, XBee Dataset from their experiment from 10 identical transceivers based on the ZigBee communication protocol, and Matrice dataset [62] containing seven identical Matrice 100 (M100 dataset) drones.
[44]	Used own experiment using 2.4 GHz operating frequency, antenna X310, receive sampling rate of 100 MSps with drones, radio controllers, and Wi-Fi Sources from 11 devices.
[45]	Used own experimental datasets.
[46]	A public dataset is used to train from DroneRF datasets (composed of 227 recorded segments collected from 3 different drones, size of datasets 3.75 GB) [57].
[47]	DroneRF datasets (composed of 227 recorded segments collected from 3 different drones, size of datasets 3.75 GB) [57], with 454 RF signal records, each consisting of 1 million samples.
[48]	Used own datasets, which were collected indoors from 14 micro-UAV controllers operating at 2.4 GHz in near-field [58]. Each controller 100 RF signals contains 5000 k samples. Training (60%) + Cross-validation (20%) and 20% for Testing).
[49]	DroneRF datasets (composed of 227 recorded segments collected from 3 different drones, size of datasets 3.75 GB) [57], containing 22700 elements and 2047 features and training, validation, and testing ratio 70%, 10%, and 20%.
[50]	Used own datasets with seven DJI drones; 500 spectrograms are generated; 90% used for training and 10% for validation.
[51]	Used DroneRF datasets [57] where out of $22,700 \times 7$ elements 90%, $20,430 \times 7$, was used for training and 2270×7 used for testing datasets.
[52]	Used own experimental datasets with trained PSD models for 6 UAVs where used 178 data points for every training example.

In recent years, the use of RF-based UAV detection and classification has dramatically increased. In the state of the art, many works have been completed using RF technology for UAV detection and classification [42,57,63–65]. A DL approach based on RF was proposed in [63] to detect multiple UAVs. To complete the objectives of detection and classification, the authors suggested the use of a supervised DL model. For RF signal preparation, they employed short-term Fourier transform (STFT). The higher efficiency of their approach was largely due to the preparation of the data, which was first conducted by using STFT. The authors in [64] introduced a model named RF-UAVNet, which was designed with a convolutional network for UAV tracking systems that used RF signals to recognize and classify the UAVs. In order to minimize the network dimensions and operational expense, the recommended setup uses clustered convolutional layer structures. This research took advantage of the publicly accessible dataset DroneRF [57] for RF-based UAV detection techniques.

The authors in [34] assessed the impact of real-world Bluetooth and Wi-Fi signal interference on UAV detection and classification by employing convolutional neural network (CNN) feature extraction and machine learning classifiers logistic regression and k-nearest neighbor (kNN). They used graphical representations in both the time and frequency domains to evaluate two-class, four-class, and ten-class flying mode classification.

In a separate study, the authors in [35] proposed a drone detection system recognizing various drone types and detecting drones. They designed a network structure using multiple 1-dimensional layers of a sequential CNN to progressively learn the feature map of RF signals of different sizes obtained from drones. The suggested CNN model was trained using the DroneRF dataset, comprising three distinct drone RF signals along with background noise.

Another investigation by the authors in [36] involved comparing three distinct classification methods to identify the presence of airborne users in a network. These algorithms utilized standard long-term evolution (LTE) metrics from the user equipment as input and were evaluated using data collected from a car and a drone in flight equipped with mobile phones. The results were analyzed, emphasizing the advantages and disadvantages of each approach concerning various use cases and the trade-off between sensitivity and specificity.

Furthermore, in [37], the researchers explored the use of artificial neural networks (ANNs) for feature extraction and classification from RF signals for UAV identification. This study distinguished itself by employing the UAV communication signal as an identification marker. Moreover, the research creatively extracted the slope, kurtosis, and skewness of UAV signals in the frequency domain. Additionally, [38] proposed the detection and classification of micro-UAVs using machine learning based on RF fingerprints of the signals transmitted from the controller to the micro-UAV. During the detection phase, raw signals were divided into frames and converted into the wavelet domain to reduce data processing and eliminate bias from the signals. The existence of a UAV in each frame was detected using a naïve Bayes approach based on independently constructed Markov models for UAV and non-UAV classes.

The authors in [39] described their efforts to locate drone controllers using RF signals. A signal spectrum monitor was used as an RF sensor array. From the sensor's output, a CNN was trained to anticipate the drone controller's bearing on the sensor. By positioning two or more sensors at suitable distances apart, it became possible to determine the controllers' positions using these bearings.

In [40], the authors proposed a drone detection method aimed at creating a database for RF signals emitted by different drones operating in various flight modes. They considered multiple flight modes in simulations and utilized the RF database to develop algorithms that detect and identify drone intrusions. Three DNNs were employed to identify drone locations, types, and flight modes.

For recognizing and identifying UAVs based on their RF signature, [41] suggested an end-to-end DL model. Different from previous research, this study employed multiscale feature extraction methods without human intervention to extract enhanced features aiding the model in achieving strong signal generalization capabilities and reducing computing time for decisionmaking.

The study in [42] utilized a compressed sensing technique instead of the conventional sampling theorem for data sampling. The researchers employed a multichannel random demodulator to sample the signal and proposed a multistage DL-based method to detect and classify UAVs, capitalizing on variations in communication signals between drones and controllers under changing conditions. Additionally, the DroneRF dataset was utilized in [42], The UAV was first identified by the DNN, and then it was further identified by a CNN model. Nevertheless, it was not feasible to take into account additional signals that appeared in the 2.4 GHz range when utilizing the DroneRF dataset [65].

In [43], the authors proposed a novel method based on RF signal analysis and multiple ML techniques for drone swarm characterization and identification. They provided an unsupervised strategy for drone swarm characterization using RF features extracted from the RF fingerprint through various frequency transforms. Unsupervised techniques like manifold approximation and projection (UMAP), t-distributed stochastic neighbor embedding (t-SNE), principal component analysis (PCA), independent component analysis (ICA), and clustering algorithms such as X-means, K-means, and mean shift were suggested to minimize input data dimension.

A study on RF-based UAV detection and classifictaion was conducted in [8], where the authors considered the interference of other wireless transmissions such as Bluetooth and Wi-Fi. They extracted and characterized the RF signals using wavelet scattering transform (WST) and continuous wavelet transform (CWT). The signal was classified and identified taking into account both transient and stable phases. In order to examine the effectiveness of coefficient-based approaches (CWT and WST), they also executed several image-based methods for extracting features. Using PCA in conjunction with several ML models, including support vector machine (SVM), KNNs, and ensemble, they completed classification and detection activities with varying degrees of noise.

In [48], the authors demonstrated the use of Markov-based naïve Bayes ML approaches for the identification and classification of UAVs using numerous RF raw signal fingerprints from various UAV controllers and under varying SNR levels. To mitigate noise sensitivity and respond with modulation approaches, the categorization specifically relied on the energy transient signal and statistically processed it. This approach avoids potential delays in identifying the transient signal, particularly in low-SNR conditions, due to its lower processing cost and not relying on the time domain. Several ML techniques, such as discriminant analysis (DA), NN, KNN classification, and SVM, were trained on the feature sets for UAV classification and detection.

In addition, low, slow, and small UAVs (LSSUAVs) operating in the 2.4 GHz frequency range can be detected slowly by using Hash Fingerprint (HF) characteristics based on distance-based support vector data description (SVDD)-based UAVs detection according to a proposal provided in [66]. The system started by identifying the primary signal's starting point, creating envelope signals, followed by removing the envelopes from the signals. The HF is then created as a characteristic to train SVDD. To evaluate the system, the authors gathered a customized dataset. The outcomes showed that the system can identify and locate LSSUAV signals within an interior setting. Nevertheless, the system efficiency was decreased when additive white Gaussian noise (AWGN) was supplied.

A framework for UAV detection based on auxiliary classifier Wasserstein generative adversarial networks (AC-WGANs) was presented in [67]. The model leverages RF fingerprints from UAV radios as input features. The popular image synthesis and analyzing tool known as the generative adversarial network (GAN) model was modified for UAV detection and multiclassification. This was accomplished by utilizing and enhancing the GAN discriminator model. PCA was utilized to further decrease the dimensionality of the RF signature for feature extraction after the intensity envelope had been used to shorten the initial signal. Four UAVs, one Wi-Fi device, and a randomly selected signal taken from the surroundings were used in their test setup. AC-WGAN was able to achieve a 95% accuracy rate of UAV detection.

A DNN model was trained using the frequency parts of the UAV RF signals that were extracted using discrete Fourier transform (DFT) in [40]. In the proposed work, three UAVs were used for the simulation. The UAV detection and classification achieved a precision of 84.5%. The authors did not take into account additional ISM devices that operate in the identical 2.4 GHz frequency range, except for UAV-flight controller communication. Furthermore, the efficacy of the framework at different signal-to-noise ratios (SNRs) was not evaluated. Additionally, the time required for inference of the classification algorithm was not considered.

2.1.1. Challenges and Solutions of RF-Based UAV Detection and Classification Using ML

- **RF signal variability:** Diverse RF signal characteristics due to variations in UAV models, communication protocols, and flight dynamics. Develop robust feature extraction methods capable of capturing and analyzing different RF signal patterns across various UAVs.

- **Background noise and interference:** Environmental noise and interference affecting the accuracy of RF-based detection systems. Investigate advanced signal processing algorithms and adaptive filtering to mitigate the impact of background noise on RF signal clarity.
- **Signal strength and distance:** RF signal attenuation over long distances limits the effective range of UAV detection systems. Explore novel antenna designs and signal amplification techniques to improve signal sensitivity and extend detection range.
- **UAV classification:** Accurately distinguishing between different UAV types based on similar RF signal features. Implement advanced machine learning models, such as deep neural networks, for fine-grained classification of UAVs using RF signatures.
- **Real-time processing:** Processing RF data in real time for prompt detection and response. Optimize machine learning algorithms and hardware configurations, possibly leveraging edge computing techniques, to enable rapid analysis of RF signals.
- **Security and adversarial attacks:** Vulnerability of RF-based systems to adversarial attacks and signal spoofing. Implement robust encryption and authentication mechanisms to secure RF signals and prevent malicious intrusions.

2.1.2. Future Directions of RF-Based UAV Detection and Classification Using ML

- **Advanced signal processing techniques:** Explore advanced signal processing methods, such as compressed sensing and adaptive filtering, to enhance the extraction of discriminative features from RF signals for more precise UAV classification [68].
- **Multisensor fusion for improved accuracy:** Investigate the fusion of RF data with other sensor modalities (e.g., optical or acoustic) to create more comprehensive and accurate UAV detection systems capable of handling diverse environmental conditions [69].
- **Dynamic adaptation and self-learning algorithms:** Develop machine learning models with adaptive learning capabilities, enabling continuous improvement and adaptation to evolving UAV signal variations, environmental changes, and new UAV models [17].
- **Real-time edge computing for swift decisionmaking:** Explore the integration of edge computing techniques with RF-based UAV detection systems to achieve faster processing speeds, enabling real-time decisionmaking in dynamic and resource-constrained environments [70].
- **Robustness against adversarial attacks:** Investigate novel approaches to fortify RF-based UAV detection systems against adversarial attacks, including intrusion detection mechanisms and cryptographic protocols [71].
- **Standardization and interoperability:** Collaborate across academia, industry, and regulatory bodies to establish standardized protocols and interoperable frameworks for RF-based UAV detection systems, facilitating compatibility and integration across different platforms [72].

2.2. UAV Classification Based on ML Using Visual Data Analysis

Due to the intricacy of radar technology and the quick advancements in computer vision, several researchers are considering the employment of visual information (images or videos) for UAV detection and classification. Because visual images have a high resolution, they are frequently utilized for semantic segmentation and object recognition. However, using visible images also comes with its own set of issues, like shifting light, obscured areas, and a cluttered background. In addition, there are usually difficulties involved in carrying out this operation in visible photographs, such as the UAV's small dimensions, the disorientation of birds, the presence of concealed regions, and busy backgrounds. For these reasons, an effective and thorough detection technique must be used. Deep CNN has recently made significant strides, and the introduction of better technology allows for faster and more accurate object detection using visual input, especially for visual-based UAV detection and classification. The basic detection and classification of UAVs based on image or video (visual data) using the ML algorithm is demonstrated in Figure 4. The summary of related research on visual-based methods using ML for UAV detection and classification is shown in Table 4. Furthermore, the dataset information of the current research on visual-based methods using ML for UAV detection and classification is shown in Table 5.

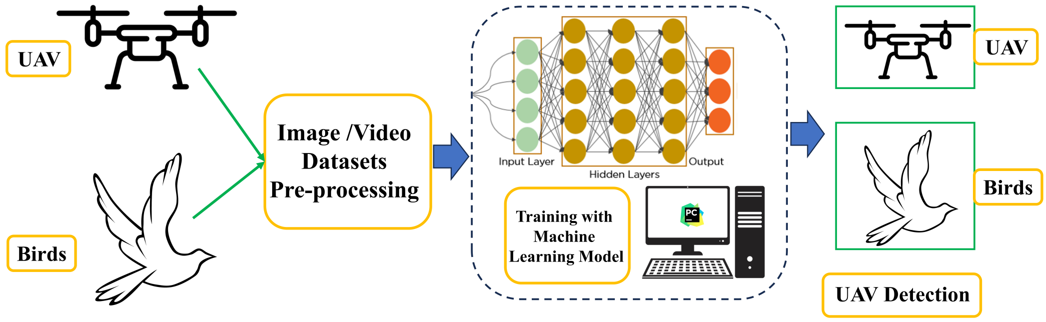

Figure 4. The detection and classification mechanism of UAV based on visual data analysis.

Table 4. Comparison summary of ML-based UAV classification and detection using visual data.

Reference	Detection Target	Machine Learning Method	Performance	Model Types [1]
[73]	Loaded and unloaded UAV detection using image	YOLOv2	Accuracy: 80.34%, mean average precision (mAP): 74.97%	SL
[74]	Small UAV detection using image	pruned yolov4	Precision: 30.7%, Recall: 72.6%, mAP: 90.5%, F1-score: 45.2%	SL, DTL
[75]	Small UAV detection using the static wide-angle camera and a lower-angle camera	lightweight YOLOv3	Can Detect Multiple UAV	SL
[76]	Flying UAV detection using fisheye camera images	CNN, SVM, and KNN	Accuracy: CNN, SVM, and KNN of 93%, 88%, and 80%, Precision: 96%, 86%, and 74%, Recall: 91%, 91%, and 94%	SL
[77]	UAV detection using RGB images	YOLOv3	Precision: 95.10%, Recall: 99.01%, mAP:74%	SL
[78]	Low-altitude UAV detection	YOLOv4, YOLOv3 and SSD	Accuracy: YOLOv4, YOLOv3, and SSD with 89.32%, 89.14%, and 79.52%, Recall: 92.48%, 89.27%, and 85.31%, mAP: 89.32%, 89.14%, and 76.84%	SL
[79]	UAV detection using images	Transfer Learning with YOLOv3	Accuracy: confidence rate (CR) within 60% to 100% and average CR of 88.9%	SL
[80]	UAV Tracking using visual data	SSD, YOLOv3, and Faster RCNN	mAP: 98%	SL
[81]	UAV detection using images	YOLOv4	Precision: 0.95, Recall: 0.68, F1-score: 0.79, and mAP: 74.36%	SL
[82]	UAV detection using images	Fine-tuned YOLOv2	Precision and recall of 0.90	SL
[83]	UAV detection using images	VGG16 with Faster R-CNN	mAP: 0.66	SL, DTL
[84]	UAV detection using video images	YOLOv2 and Darknet19	Precision:88.35%, Recall: 85.44%, F1-score: 73.3%	SL, DTL
[85]	UAV detection using images	Faster RCNN	Precision recall: 0.93	SL

Table 4. *Cont.*

Reference	Detection Target	Machine Learning Method	Performance	Model Types [1]
[86]	UAV detection using images	RetinaNet, SSD, YOLOv3, FPN, Faster R-CNN, RefineDet, Grid R-CNN, and Cascade R-CNN	Grid R-CNN achieves best accuracy 82.4% among all detectors, while RefineDet 69.5%. Among 2-stage models, Cascade R-CNN achieved best accuracy 79.4%, whereas Faster R-CNN achieved worst 70.5%. For 1-stage models, SSD512 78.7%and RetinaNet 77.9% both perform well, whereas YOLOv3 achieved only 72.3%	SL, DTL
[87]	UAV detection using images	YOLOv4	Accuracy: 83% Recall: 84%, mAP: 84%, F1-score: 83%, and Intersection over Union (IoU): 81%	SL
[88]	UAV detection using image data	YOLOv5 and v7	Precision: 95%, Recall: 95.6%, mAP: 96.7%	SL
[89]	UAV detection using image data	YOLOv4	Average precision: 34.63%	SL
[90]	UAV Vs. Bird detection using image data	Cascade R-CNN, YOLOv5, and YOLOv3	Detection results of Cascade R-CNN, YOLOv5, and YOLOv3 were 79.8%, 66.8%, and 80.0%	SL
[91]	UAV detection using image	Deep clustering (YOLOv8 + t-SNE)	Accuracy: 100%	USL

[1] SL = supervised learning, USL=unsupervised learning, DTL=deep transfer learning.

Table 5. Datasets information of ML-based UAV classification and detection using visual data.

Reference	Datasets Information
[73]	Used own experimental dataset from flying multifunctional Quad-rotor system DJI Phantom 2 and the total number of images for each class was 1000.
[74]	Used own experimental dataset with 10 thousand images of drones, 8000 images used for training and 2000 for testing.
[75]	Used own experimental dataset where the raw main image plane size was 1600 × 1600 pixels; it was automatically downsized to 832 × 832 pixels; testing completed with 800 frames from 20 videos.
[76]	Used own experimental dataset, which contained drone and bird images where 712 images of drones and birds were collected and 80% of these data used for training and 20% for testing.
[77]	The dataset was created by gathering images from the internet and removing frames from various drone recordings. More than 10,000 images featuring various drone genres were available.
[78]	Used own and public datasets with a total of 1540 visible images obtained, encompassing a range of flight attitudes such as fast descent, angle rotation, fast flight, steady combat, low-altitude hovering, and high-altitude hovering. Further expansion dataset collected 556 drone images from the internet.
[79]	Images of drones, hexacopters, quadcopters, and UAV images were collected. A total of 1500 images drone images were manually sorted to remove extrinsic images, and 1435 images were prepared where data augmentation enhanced the 1435 to 7175 images, and 19.5% of the dataset used for validation and 80.5% as training.
[80]	Datasets contained three data: (a) MAV-VID, (b) Drone vs. Bird, (c) Anti-UAV Visual. For Anti-UAV, size of training: 60 videos (149,478 images), validation: 40 videos (37,016 images), and average object size (AOS) of RGB: 125 × 59 pxs (0.40% image size), IR: 52 × 29 pxs (0.50% image size). For Drone vs. Bird, size of training: 61 videos (85, 904 images), validation: 16 videos (18,856 images), and AOS of 34 × 23 pxs (0.10% of image size). For MAV-VID, size of training: 53 videos (29,500 images), validation: 11 videos (10,732 images), and AOS of 215 × 128 pxs (3.28% of image size). For information about datasets, openly accessible from [92].
[81]	Used datasets from Google and Kaggle [93]; collected 2395 images consisting of 479 birds and 1916 drones and dataset split into 90% for training and 10% for testing.
[82]	Dataset collected public domain pictures of drones and birds and videos of coastal areas with a total of 676, 534 images. The dataset was divided into training 85% and validation 15%.

Table 5. *Cont.*

Reference	Datasets Information
[83]	Used datasets with experimentation on Bird vs. Drone. The dataset contains 5 MPEG4-coded videos taken at different times, 2727 frames with a resolution of 1920 × 1080.
[84]	Used two datasets: one was from the public domain called USC Drone Dataset [94] comprising 30 YouTube video segments that feature diverse drone models with diverse appearances. These video clips have a frame resolution of 1280 × 720. The other built by authors; shot 49 experimental videos with HIKVISION DS-2DF7330IW Network PTZ camera where, for the mainstream and substream, the frame resolutions were 2048 × 1536 and 1024 × 768.
[85]	Used two datasets: public domain drone dataset comprising 30 YouTube videos captured in indoor or outdoor environment with frame resolution of 1280 × 720. The other was from USC Drone Dataset [94], which contained 30 video clips shot at the USC campus with frame resolutions 1920 × 1080 and frame rate was 15 FPS.
[86]	Used dataset called Det-Fly [95], which includes 13, 271 images of a target micro-UAV (DJI Mavic). Every image in the collection contains 3840 × 2160 pixels, and some of them are taken at 5 FPS from videos.
[87]	Used drone and bird visible image datasets where drone dataset used several multirotors, helicopters for training; 70% used for training and 30% for validation.
[88]	Used datasets of quadcopter images where datasets taken from Kaggle [96] and self-builds from camera. The dataset contained 1847 images and the training and validation ratio was 80% and 20%, respectively, and the training set was expanded to 4753 images using hue augmentation, which produced two additional images for each image.
[89]	Used own dataset images of drones that were downloaded from the internet. They gathered labeled images of quadcopter drones with varying sizes and backgrounds. The datasets comprised approximately 4500 color images of drones where 1350 drone images were used for testing and 3150 for training.
[90]	Gradiant Team: Utilized Purdue UAV dataset [97] comprised of 70,250 frames in total, which were then subsampled to yield 27,864 frames with 10,461 bounding boxes, and private data comprised 14,152 bounding boxes and 22,236 frames. EagleDrone Team: Used three open-source datasets including Little Birds in Aerial Images, Drone vs. Bird Competition dataset, and Birds in the background of the Windmills dataset. Alexis Team: A total of 106,485 frames were eliminated by the Alexis team out of the 77 available annotated sequences. The Cut, Paste, and Learn paper was followed by the Alexis team to create 26,500 synthetic images [98].

The recent advancements in ML models have significantly enhanced the capability to detect and classify UAVs in both secure areas and public environments. With the emergence of more powerful deep CNNs and the availability of superior equipment, the process of identifying objects through visual input can now be accomplished with greater speed and accuracy [73]. DL networks are specifically designed for instantaneous UAV recognition, distinguishing them from traditional UAV detection systems. These networks classify inputs into various UAV classes, identifying the category, position, as well as the presence or absence of different UAV types [99]. CNNs are among the most significant NN models for image detection and categorization. The input information for this network passes through the convolutional layers. Next, the network's kernel is used to execute the convolution function in order to detect commonalities. Finally, the generated feature map is used for feature extraction [100]. CNNs come in several varieties, including region-based CNN (R-CNN) [101], spatial syramid sooling network (SPPNet) [102], and Faster RCNN [103]. Convolutional procedures are applied in these networks, enabling the extraction of additional information and improving both speed and precision in object detection compared to traditional techniques. Practically, the extracted features serve as object descriptors for recognition. Region proposal networks (RPNs) are employed in these networks to initially define suggested regions [104]. Following the application of convolutional filters to such locations, the convolutional process yields the extracted features [103]. Additional DL methods, including you only look once (YOLO) [105] and SSD (single-shot multibox detector) [106], often examine the image, leading to faster and more accurate item detection than simple techniques [105]. In recent times, the detection of UAVs has emerged as a promising field within the research community. Numerous studies have been conducted for UAV detection and classification [73–79,82,83].

Several obstacles, including the UAVs' tiny dimensions in various images, could be too small for the YOLOv4 DL network to detect [74]. In this investigation [74], the network was unable to identify the UAV in a few of the challenging images. These difficulties are due to the fact that, due to their small size, some drones can be mistaken for birds and may be found in concealed or cluttered environments. To address the challenge of identifying flying UAVs more effectively, the YOLOv4 DL network underwent significant changes. The primary innovation in this study lies in the modification of the network design. Additionally, this research successfully identified four types of multirotors, which include fixed-wing, helicopter, and VTOL (vertical take-off and landing) aircraft.

By employing the YOLOv3 DL system, an autonomous UAV detection system was implemented in [75]. One of the benefits of this study is its affordability due to the system's low requirement for GPU memory. The study successfully detected tiny-sized UAVs operating at close range. However, a limitation of this research is the inability to accurately identify different types of UAVs.

The study in [76] utilized CNNs, SVMs, and nearest-neighbor algorithms for UAV identification using fisheye cameras. The experimental results demonstrated that the efficiency of CNN, SVM, and nearest-neighbor algorithms was 93%, 88%, and 80%, respectively. The CNN classifier exhibited good precision when compared to different classifiers operating under the same test settings. It is worth noting that this study did not take into account different types of UAVs or account for various detection challenges; it solely focused on UAV detection.

Utilizing the YOLOv3 DL network, the study in [77] successfully identified and categorized UAVs in RGB images, achieving a mean average precision (mAP) of 74% after completing 150 epochs. It is worth noting that the paper did not delve into the topic of differentiating UAVs from birds; rather, it focused solely on the identification of UAVs at varying distances. Furthermore, the study in [78] addressed low-altitude UAV detection using the YOLOv4 deep learning network. For performance comparison, the YOLOv4 detection results were contrasted with those of the YOLOv3 and SSD models. The investigation revealed that the YOLOv4 network outperformed both the YOLOv3 and SSD networks in terms of mAP and detection speed. In the simulation, YOLOv4 achieved an impressive 89.32% mAP in the detection, recognition, and identification of three different types of UAVs.

In [79], the YOLOv3 DL network was employed to detect and track a UAV. The study utilized the NVIDIA Jetson TX2 for real-time UAV detection. Based on the findings, it can be concluded that the proposed YOLOv3 DL network achieved an 88.9% average confidence score and demonstrated an accuracy range of 60% to 100% for detecting UAVs of small, medium, and large sizes, respectively. In addition, employing four DL network architectures in conjunction with a dataset comprising both visual and thermal images, the study outlined in [80] successfully detected and classified UAVs. This investigation harnessed the power of DL networks such as DETR (DEtection TRansformer), SSD, YOLOv3, and Faster RCNN models for superior detection performance. The results demonstrated that even diminutive UAVs could be reliably detected from a considerable distance by all the networks under scrutiny. Notably, YOLOv3 exhibited the highest overall accuracy, boasting an impressive mAP of up to 0.986, while Faster RCNN consistently demonstrated the highest mAP for detecting tiny UAVs, peaking at 0.770.

In [81], the authors utilized YOLOv4 to develop an automated UAV detection technology. They evaluated the algorithm on two distinct types of UAV recordings, employing a dataset containing images of both drones and birds for UAV identification. The findings from this study for the detection of two different kinds of multirotor UAVs are as follows: precision of 0.95, recall of 0.68, F1-score of 0.79, and mAP of 74.36%. In [82], the authors proposed an extension of the single-shot object detector CNN model, known as YOLO. They introduced a regression training approach for UAV identification in the latest version, YOLOv2, using fine-tuning. With the use of an artificial dataset, they were able to achieve similar accuracy and recall values, both at 0.90, in their technique evaluation.

In order to detect the UAVs from video data, the authors in [83] examined a variety of pre-trained CNN models, such as Zeiler and Fergus (ZF) and VGG16 combined with the Faster R-CNN model. To make up for the absence of a large enough dataset and to guarantee convergence throughout the model's training process, they employed the VGG16 and the ZF model as transfer learning models. The Nvidia Quadro P6000 GPU was used for the training, and a batch size of 64 was used with a fixed learning rate of 0.0001. They used the Bird vs. UAV dataset, which is made up of five MPEG4-coded films with a total of 2727 frames and 1920 $\times$ 1080 pixel quality, shot during various sessions.

The study in [87] proposed a novel DL-based technique for effectively identifying and detecting two different types of birds and drones. When the suggested method was evaluated using a pre-existing image dataset, it outperformed the detection systems currently utilized in the existing literature. Moreover, due to their similar appearance and behavior, drones and birds were often mistaken for each other. The proposed technique can discern and differentiate between two varieties of drones, distinguishing them from birds. Additionally, it can determine the presence of drones in a given location.

To detect small UAVs, [88] utilized various iterations of state-of-the-art object detection models (like YOLO models) using computer vision and DL techniques. They proposed different image-processing approaches to enhance the accuracy of tiny UAV detection, resulting in significant performance gains.

2.2.1. Challenges and Solutions of Visual Data-Based UAV Detection and Classification Using ML

- **Variability in visual data:** Visual data captured by cameras vary due to factors like lighting conditions, weather, angles, and distances, making consistent detection and classification challenging. Employ robust preprocessing techniques (e.g., normalization and augmentation) to standardize and enhance visual data quality.
- **Limited annotated datasets:** The lack of diverse and well-annotated datasets specific to UAVs hampers the training of accurate ML models. Develop and curate comprehensive datasets encompassing various UAV types and scenarios for effective model training.
- **Real-time processing:** Processing visual data in real time for swift and accurate UAV detection and classification. Optimize algorithms and hardware configurations to ensure real-time processing capabilities, potentially leveraging GPU acceleration or edge computing.
- **Scale and complexity:** Scaling detection and classification algorithms to handle complex scenes, multiple UAVs, or crowded environments. Explore advanced DL architectures capable of handling complex visual scenes for improved detection and classification accuracy.
- **Adaptability to environmental changes:** Adapting to environmental changes (e.g., varying weather conditions) affecting visual data quality and system performance. Develop adaptive algorithms capable of adjusting to environmental variations for robust and reliable detection.

2.2.2. Future Directions of Visual Data-Based UAV Detection and Classification Using ML

- **Multimodal integration:** Integrate visual data with other sensor modalities (e.g., RF or LiDAR) for more comprehensive and reliable UAV detection systems [107].
- **Semantic understanding and contextual information:** Incorporate semantic understanding and contextual information in visual analysis to improve classification accuracy [108,109].
- **Ethical and privacy concerns:** Address privacy considerations by implementing privacy-preserving techniques without compromising detection accuracy [110].
- **Interpretability and explainability:** Develop methods for explaining and interpreting model decisions, enhancing trust and transparency in visual-based UAV detection systems [111].

2.3. UAV Classification Based on ML Using Acoustic Signal

UAVs emit a distinctive buzzing sound during flight, which can be captured by acoustic sensors and subjected to various analyses to establish a unique audio signature for each

UAV. The capability to identify a UAV based on its auditory fingerprint, or even determine its specific type, would be highly valuable. Figure 5 illustrates an example of a machine learning-based approach for UAV detection and classification using the acoustic method. Furthermore, Table 6 provides a summary of related research on acoustic-based methods employing machine learning for UAV detection and classification. In addition, the dataset information of the current research on acoustic-based methods using ML for UAV detection and classification is shown in Table 7. In the realm of audio-based UAV identification, DL techniques are commonly employed to extract features and achieve optimal UAV detection performance. Recent studies [112–118] also demonstrated the efficacy of DL models in extracting characteristics from UAV audio signals for UAV identification.

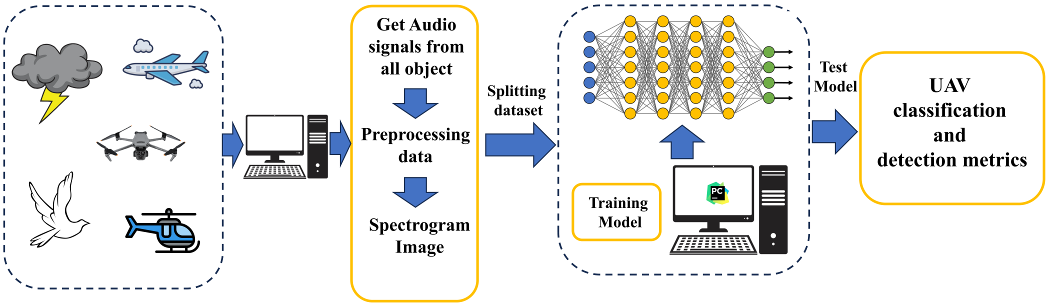

Figure 5. The detection and classification mechanism of UAV based on acoustic data analysis.

Table 6. Comparison summary of ML-based UAV classification and detection using acoustic data.

Reference	Detection Target	Machine Learning Method	Performance	Model Types [1]
[119]	UAV detection using acoustic fingerprints	CNN, RNN, and CRNN	Accuracy: CNN, RNN, and CRNN 96.38%, 75.00%, 94.72%, Precision: 96.24%, 75.92%, 95.02%/95.60%, Recall: 95.60%, 68.01%, 93.08%, F1-score: 95.90%, 68.38%, 93.93%	SL
[112]	UAV detection using audio fingerprints	MFCC with CNN	Accuracy: 94.5%	SL
[113]	Amateur UAV detection using acoustic	LWCNN + SVM	Accuracy: 98.35%, Precision: 98.50%, Recall: 98.20%, F1-score: 98.35%	SL
[115]	UAV detection using acoustic	SVM	Accuracy: 97.8%, Precision: 98.3%	SL
[120]	Amateur UAV detection using acoustic	FTT and KNN method	Precision: 83.0%	SL
[121]	Amateur UAV detection using sound	MFCC and LPCC with SVM	Accuracy: 97.0%, Recall: 100%	SL
[114]	UAV classification using sound	GMM, CNN, and RNN	Accuracy: RNN, CNN, GMM 0.8109, 0.5915, 0.6932, Precision, recall of RNN (0.7953, 0.8066), CNN and GMM precision (CNN, GMM: 0.5346 $<$ 0.9031) and recall (CNN, GMM: 0.8019 $>$ 0.3683), F1-score: RNN $>$ CNN $>$ GMM: 0.8009 $>$ 0.6415 $>$ 0.5232	SL
[122]	UAV classification using acoustic STFT features	CNN	Accuracy: 98.97%	SL

Table 6. *Cont.*

Reference	Detection Target	Machine Learning Method	Performance	Model Types [1]
[117]	UAV detection using multiple acoustic notes	SVM, CNN	Accuracy of SVM with STFT and MFCC of F1-score 78.70% and 77.90%	SL
[16]	UAV detection using acoustic	SVM, CNN	Accuracy: 94.725%, F1-score: 94.815%	SL
[118]	UAV detection using acoustic	Plotted image machine learning (PIL) and KNN	Accuracy of PIL and KNN of 83% and 61%	SL
[123]	UAV detection using acoustic	To generate the artificial UAV audio dataset, implemented a GAN model + CNN, RNN, and CRNN	Accuracy: 0.9564, Precision: 0.9783, Recall: 0.9738, F1-score: 0.9753	SL
[124]	UAV detection using acoustic signature	MFCCfeatures with SVM	Accuracy: 99.9%, Recall: 99.8%, Precision: 100%	SL
[125]	UAV detection using acoustic signature	SVM	Accuracy: 95.6%	SL
[126]	UAV detection using acoustic	SVM	Accuracy: 93.53%, Recall: 90.95%, F1-score: 93.19%	SL
[127]	UAV detection using acoustic signal	MFCC with concurrent neural networks (CoNN)	Accuracy: 94.95%, Precision: 93.00%, Recall: 89.00%, F1-score: 91.00%	SL
[128]	UAV detection using acoustic data	MFCC with multilayer perception (MLP) and balanced random forest (BRF) algorithm	Accuracy of MLP and BRF were 0.83% and 0.75%	SL
[129]	UAV detection using acoustic features	MFCC with CNN model	Accuracy: 80.00%, Precision: 90.9%, Recall: 66.7%, F1-score: 76.9%	SL
[130]	UAV detection using acoustic features	SVM	Accuracy: 86.7%	SL
[131]	UAV detection using sound signals	MFCC, Mel, Contrast, Chroma, and Tonnetz features with NN, SVM, a Gaussian naïve Bayes (GNB), and, KNN	Accuracy: SVM, GNB, KNN, NN of 100%, 95.9%, 98.9%, 99.7%, Precision: SVM, GNB, KNN, NN of 100%, 95.3%, 99.5%, 99.5%, Recall: SVM, GNB, KNN, NN of 100%, 96.8%, 98.4%, 100%, F1-score: SVM, GNB, KNN, NN of 100%, 96.0%, 98.9%, 99.7%	SL
[132]	UAV detection using acoustic	Lightweight CNN	Accuracy: 93.33%	SL
[133]	UAV detection using acoustic	Linear, MLP, RBFN, SVM, and Random Forest	Detection probability of error with 1m range between 20% and 30%	SL
[134]	UAV detection using acoustic	Transformer-based CNN model	F1-score of 88.4%	SL

[1] SL = supervised learning, DTL = deep transfer learning.

Table 7. Datasets information of ML-based UAV classification and detection using acoustic data.

Reference	Datasets Information
[119]	The acquired dataset was 1300 drone sound clips from [135]. To replicate actual scenarios, the drone audio samples were artificially enhanced with noise using publicly accessible noise datasets [136,137]. After reformatting, the sampling rate of audio was 16 KHz, and bitrate was 16 Kbps. The training, validation, and testing set ratios were 70%, 15%, and 15%.
[113]	Used two different datasets: the first dataset consists of bird, airplane, storm, drone, helicopter, and background object classes, and the second dataset was obtained by flying Parrot Bebop and Mambo drones indoors [119]. The total dataset size consists of 3040 samples and dataset split into 70% training and 30% validation.
[115]	Datasets produced in the surrounding environment were picked up by an audio sensor. A sampling rate of 48 kHz and linear encoding with 16 bits for the sample were maintained. A total of 4272 samples of audio frames were collected from 5 different classes: drone flying, nature daytime, street with traffic, train passing, and crowd.

Table 7. *Cont.*

Reference	Datasets Information
[120]	Datasets contained the microphone audio recording signals from several sources, including airplanes, birds, wind, rain, thunder, and the AmDr. Each of the sources has 10,000 samples. These signals are obtained through free downloads from various databases [138,139].
[121]	Acoustic data dataset was collected from 4 different sets of sound data: birds, drones, thunderstorms, and airplanes in a real noisy environment. Training with a total of 138 samples, and testing used 34 sound samples. The length of the samples varies, but the highest duration was 55 seconds.
[114]	Training dataset augmented with raw background and drone sound. The background sound is a combination of data from own recording and a publicly available dataset [140,141] for DJI, Phantom3, and Phantom4 devices. There were 9556 seconds of audio used in total for training.
[122]	Datasets collected from own experiment with sampling rate 44,100 Hz and at 10 second intervals. There were 882 samples of 20 ms frames with 50% overlap in the reconstructed data. The non-drone sound dataset was 41,958 frames, whereas the drone sound was 68, 931 frames.
[117]	Dataset was collected in person, and 6 listening nodes were positioned close to one another to record audio for the training data. The test data consisted of audio recordings from the 6nodes, arranged in various configurations to form a circle or half circle. The UAV was flown between each node at a maximum distance of 20 m and an altitude of 0 to 10 m above the node.
[16]	Training Datasets: UAV class of audio with Multirotor UAV-1, Multirotor UAV-1 + Background-1, No UAV Background-1, Extra Background-2 size of 3410, 16,560, 16,560, 3410, and a total of 39,940 seconds.
[118]	Dataset in a Type 1 test, a DJI Phantom 2 drone without propellers was used, and in a Type 2 test, a YouTube video clip titled "European football atmosphere [HD]" was used. Trained 70 cases of each drone's appearance and non-appearance for the PIL ML method. For KNN training, two types of sound data were collected. The first type is drone-detected sound data. The drones used were "DJI Phantom 1 and 2" and the type of data collected were non-drone sound data. Sound data utilized 70% for training and left 30% for testing.
[123]	Used two commercially available drones, Bebop and Mambo, to collect acoustic data and created datasets of "RG Drone Audio Dataset" and "R4 Drone Audio Dataset" using GAN. In "RG Drone Audio Dataset", recorded drone clips and GAN drone clips combined created a total of 6603 for 4experiments. In "R4 Drone Audio Dataset", created a total of 5603 for 4 experiments. The training, validation, and testing ratios were 70%, 30%, and 20%. More details of datasets in [135].
[124]	For the positive (drone audio) and negative (non-drone audio) classes, 2 datasets were used. The drone audio database provided the drone acoustic datasets [135]. Noisy drone samples were taken from publicly available [137]. The samples have a 44.1 kHz sampling rate. The ESC-50 database was used for non-drone audio datasets [136]. In total, for the training 2664 audio files, 1332 acoustic samples for each of the two classes.
[125]	A database comprising 7001 drone flight observations and 3818 noise recording observations in a regulated setting where signals are played 1 at a time was created and each observation consisted of a 0.2 s signal sequence.
[126]	UFive different drone models are included in the training materials: the ALIGN M690L Multi-Drone, the SKY-HERO Little Spyder, the DJI Phantom4, the DJI Mavic, and a custom-built racing drone. Several UAV types that were absent from training dataset recordings are included in the testing material (DJI F450, Unique Taifun H520). For testing, three UAV kinds that were not in the training set were employed. A total of 1.9 h were spent recording UAV emissions, of which 68% came from the training dataset and the remaining 48% from the test dataset.
[127]	The datasets were established using the Wigner–Ville spectrogram, MFCC, and MIF dictionaries, and training data were collected for 6 different drones with different flying distances (0 to 25 m, 25 to 50 m, 50 to 100 m, 100 to 200 m, and 200 to 500 m). The models of drones were a DJI Phantom 2 (small class), a DJI Matrix 600 (medium class), and a handmade drone (medium class). The sampling frequency of the training data was 44 kHz.
[128]	The database was derived from datasets 1 and 2, which were two publicly available in [119,142]. The drones in Dataset 1 were Parrot Bebop and Parrot Mambo, with an audio duration of 11 minutes and 6 seconds. The drones in Dataset 2 were the DJI Mavic Pro, DJI Spark, DJI Matrice 100, Parrot Bebop 2, and DJI Phantom 4, each of which had 12 signals for 30 s. The No-Drone signals were from YouTube and the BBC sound database. In total, 26 MFCCs were taken out of the audio signals, and the data were classified as No-Drone and Drone.
[129]	Used a 3DR Iris+, DJI Inspire 2, and A DJI Phantom 4 to record drone sounds using a microphone. The ESC-50 dataset [136] includes environmental sounds. The dataset contained a 10-second recorded audio clip, which was divided into 5 equal parts.
[130]	The audio data collection of drone noises under 1500 Hz frequency with interval 130–180 Hz was produced with a 3DR Iris+ drone. The Iris+ measures ambient sound levels on average at 39.4079 dB outdoors and 33.0261 dB indoors. The drones Holystone Predator, DJI Inspire 2, Parrot Bepop 2, and DJI Inspire 2 were employed for detection. An audio recording per second for 14,932 was produced to train the model.
[131]	Used an EVO 2 Pro and a DJI Phantom 4 to record audio and collected 300 sound samples from each UAV, a Total of 600 sound samples and 102.67 min of recording time; 591 noise samples totaling 201.16 min were gathered. The UAV was deployed at McAllister Park, Lafayette, IN 47,904, and background noise samples were taken.

The authors in [119] created spectrograms from audio samples and fed them into DL models. The system extracted various characteristics from the spectrograms generated by the audio sources and used them to train DL models. Additionally, the authors in [113] employed an STFT to convert the audio signal into the Mel spectrum, creating a visual representation. This image was then input into a specifically designed lightweight (LWCNN) for identifying signal attributes and UAV detection.

To categorize the auditory signals as suggestive of UAV activity or not, the authors in [112] employed Log Mel spectrograms and Mel frequency cepstral coefficients (MFCC) considered as input and fed them to the CNN model. Additionally, for amateur UAV identification, the authors in [115] suggested a method that combines ML techniques with acoustic inputs. Nevertheless, the distinction between things that can be mistaken for ambient noise and other UAVs was not taken into account in their investigation.

A KNN-based method and Fast Fourier Transform (FFT) were presented in the study [120] for UAV detection using auditory inputs. Using SVM and KNN based on the auditory inputs, the signals are classified to determine whether the amateur UAV is present or not. An amateur UAV is detected based on the similarities that the acquired spectral pictures have to one another; nonetheless, the precision of this technique is only up to 83%. In order to discriminate between the sounds of items such as UAVs, birds, aircraft, and storms, the authors in [121] suggested an ML-based UAV identification system. The MFCC and linear predictive cepstral coefficients (LPCC) feature extraction techniques are used to extract the required characteristics from UAV sound. Then, SVM with different kernels is used to precisely identify these sounds after feature extraction. The findings of the experiment confirm that the SVM cubic kernel with MFCC performs better for UAV identification than the LPCC approach, with an accuracy of about 97%.

The authors in [114] proposed a method for identifying the presence of a UAV within a 150-meter radius. They suggested employing classification techniques such as the Gaussian mixture model (GMM), CNN, and RNN. To address the scarcity of acoustic data from UAV flights, the authors recommended creating datasets by blending UAV sounds with other ambient noises. One intriguing aspect of their research involves the use of diverse UAV models for training and evaluating the classifiers. Their findings revealed that the RNN classifier exhibited the highest performance at 0.8109, followed by the GMM model at 0.6932, and the CNN model at 0.5915. However, in scenarios involving unidentified information, the accuracy of all the predictors experienced a significant drop.

To produce 2-dimensional (2D) pictures from UAV audio data, the authors in [122] suggested the normalization STFT for UAV detection. Firstly, the audio stream was split into 50% overlapping 20 ms pieces. After that, a CNN network that had been created was fed the normalization STFT as an input. Evaluations from outside using DJI Phantom 3 and Phantom 4 hovering were included in the dataset, and 41, 958 non-UAV frames and 68, 931 UAV audio frames were present in the datasets.

In [123], the authors provided a hybrid drone acoustic dataset, combining artificially generated drone audio samples and recorded drone audio clips using GAN, a cutting-edge DL technique. They explored the efficacy of drone audio in conjunction with three distinct DL algorithms (CNN, RNN, and CRNN) for drone detection and identification and investigated the impact of their suggested hybrid dataset on drone detection.

The author proposed an effective drone detection technique based on the audio signature of drones in [124]. To identify the optimal acoustic descriptor for drone identification, five distinct aspects were examined and contrasted. These included MFCC, Gammatone cepstral coefficients (GaCC), linear prediction coefficients, spectral roll-off, and zero-crossing rate as chosen features. Several SVM classifier models were trained and tested to assess the individual feature performance for effective drone identification. This was completed using 10-fold and 20% data holdout cross-validation procedures on a large heterogeneous database. The experimental outcome indicated that GaCCs were the most effective features for acoustic drone detection.

In addition, AWGN was added to the dataset before conducting the testing. With a detection rate (DR) of 98.97% and a false alarm rate (FAR) of 1.28, the best results were obtained when training the CNN network with 100 epochs and low SNR ranges.

In [117], a method was proposed to optimize numerous acoustic nodes for extracting STFT characteristics and MFCC features. Subsequently, the extracted characteristics dataset was used to train two different types of supervised classifiers: CNN and SVM. In the case of the CNN model, the audio signal was encoded as 2D images, incorporating dropout and pooling layers alongside two fully connected and two convolution layers. In the initial instance, the UAV operated at a maximum range of 20 m, hovering between 0 and 10 m above the six-node acoustic setup. The Parrot AR Drone 2.0 was one of the UAVs that was put to the test. Numerous tests were carried out, and the outcomes show that the combination of SVM and STFT characteristics produced the best outcomes, as expressed in terms of color maps.

In addition, the authors in [16] explored the use of DL techniques for identifying UAVs using acoustic data. They employed Mel spectrograms as input features to train DNN models. Upon comparison with RNNs and convolutional (CRNNs), it was demonstrated that CNNs exhibited superior performance. Furthermore, an ensemble of DNNs was utilized to assess the final fusion techniques. This ensemble outperformed single models, with the weighted soft voting process yielding the highest average precision of 94.725%.

In order to differentiate between the DJI Phantom 1 and 2 models, the authors in [118] suggested KNN classifier techniques in conjunction with correlation analysis and spectrum images derived from the audio data. They collected ambient sound from a YouTube video, as well as various sound signals from both indoor settings (without propellers) and outdoor environments, including a drone-free outdoor setting. Each sound was recorded and subsequently divided into one-second frames. By utilizing image correlation methods, they achieved an accuracy of 83%, while the KNN classifier yielded an accuracy of 61%.

2.3.1. Challenges and Solutions of Acoustic Signals-Based UAV Detection and Classification Using ML

- **Signal variability:** Acoustic signals from UAVs can vary significantly based on factors like drone model, distance, environmental noise, and flight dynamics. Develop robust feature extraction methods to capture diverse acoustic signal patterns and account for variations in different UAV types.
- **Background noise and interference:** Environmental noise and interference can obscure UAV acoustic signatures, affecting detection accuracy. Employ noise reduction algorithms and signal processing techniques to filter out background noise and enhance the signal-to-noise ratio for improved detection.
- **Distance and signal attenuation:** Acoustic signals weaken with distance, limiting the effective detection range for UAVs. Explore advanced signal processing methods and sensor technologies to compensate for signal attenuation and improve detection range.
- **UAV classification from acoustic signatures:** Accurately classifying different types of UAVs based on similar acoustic features. Implement machine learning models capable of discerning subtle acoustic signal variations for precise classification, possibly utilizing DL architectures.
- **Real-time processing:** Achieving real-time processing of acoustic signals for timely detection and response. Optimize machine learning algorithms and hardware to enable faster processing speeds, potentially leveraging edge computing for quicker decisionmaking.
- **Environmental variations:** Adaptability to changes in environmental conditions (e.g., wind and temperature) affecting acoustic signal characteristics. Develop adaptive algorithms capable of adjusting to environmental variations to ensure robust and reliable detection.

2.3.2. Future Directions of Acoustic Signals-Based UAV Detection and Classification Using ML

- **Sensor fusion and multimodal integration:** Combine acoustic data with information from other sensors (e.g., visual or RF) to create more comprehensive and reliable UAV detection systems [143].
- **Advanced machine learning techniques:** Investigate advanced machine learning algorithms capable of handling complex acoustic data for improved classification accuracy [123].
- **Privacy and ethical considerations:** Address privacy concerns related to acoustic surveillance by implementing privacy-preserving methods without compromising detection accuracy [110].

- **Robustness against adversarial attacks:** Investigate methods to secure acoustic signals and machine learning models against potential adversarial attacks or spoofing attempts [144].

2.4. UAV Classification Based on ML Using Radar

Radar-based techniques rely on measuring the radar cross-section (RCS) signature to recognize airborne objects through electromagnetic backscattering. Radar offers several advantages, such as wide coverage in both azimuth and elevation planes, extended detection ranges, and the ability to operate effectively in adverse conditions like fog, where visibility is poor. This sets it apart from other UAV detection methods such as acoustics and video camera (computer vision) strategies.

However, the identification of UAVs using RCS is more challenging compared to airplanes, primarily due to their smaller dimensions and the use of low-conductivity materials, resulting in a lower RCS. In [145], it was found that the micro-Doppler signature (MDS) with time-domain analysis outperforms the Doppler-shift signature in enhancing the discrimination between clutter and targets. However, recently, ML-based UAV detection and classification tasks using radar have received more attention due to the overcoming of challenges in detection tasks and providing high-precision systems. The example detection scenario of the ML-based radar detection mechanism is shown in Figure 6. Additionally, a summary of related research on radar-based methods using ML for UAV detection and classification is shown in Table 8. Moreover, the dataset information of current research on radar-based methods using ML for UAV detection and classification is shown in Table 9. However, many works have been conducted based on ML techniques for the detection of UAVs using radar technology [146–155].

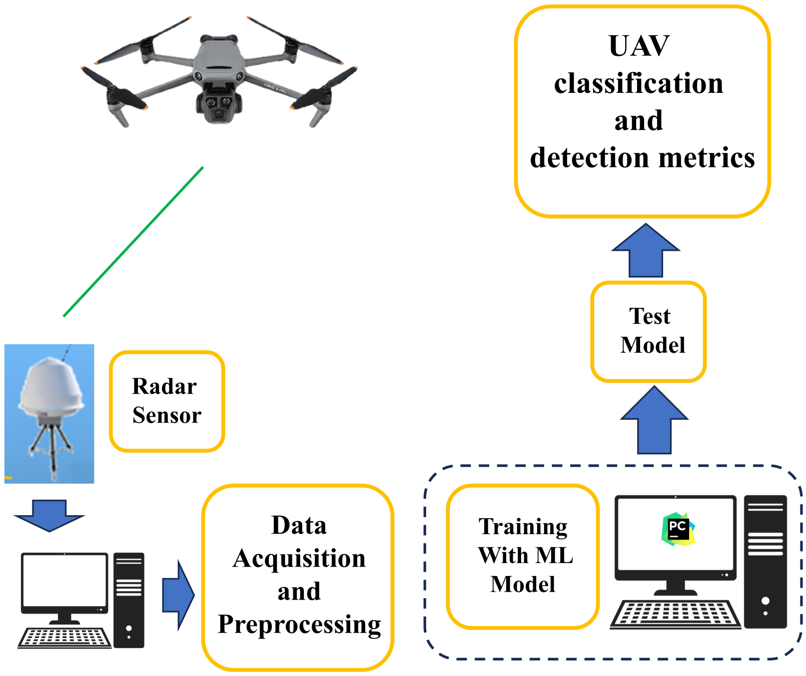

Figure 6. The detection and classification mechanism of UAV based on radar data analysis.

Table 8. Comparison summary of ML-based UAV classification and detection using radar data.

Reference	Detection Target	Machine Learning Method	Performance	Model Types [1]
[146]	UAV recognition using radar	DT and SVM	The one-stage DT and two-stage DT acquired a true positive classification rate of 81.83% and 85% with a false positive rate of 0.87% and 0.37%	SL
[147]	UAV recognition using radar	Frequency Modulated Continuous Wave (FMCW) + CNN	Accuracy: 96.86% with computation time 3.2 ms	SL
[148]	UAV recognition using radar cross-section (RCS) signature	complex-valued CNN	Accuracy: 93.80%	SL
[149]	Small UAV (SUAV) detection using radar	DCNN-DIAT-RadSATNet	Accuracy: 97.3%, Precision and recall: 97.0%, F1-score: 97.3%	SL
[150]	Tiny UAVs detection using radar	LSTM+EMD	Accuracy: CNN, SVM, LSTM of 92.6%, 90.4%, 93.9% and F1-score: 99.95%, 99.86%, 99.95%	SL
[151]	3 different UAV: DJI inspire-1, DJI inspire-2, and DJI spark detection using radar	FMCW, and micro-Doppler signature (MDS) with CNN	Accuracy: 97.14%	SL
[152]	DJI Phantom 3 detection using radar	pulse-Doppler radar, nonmaximum suppression (NMS) with CNN	False alarm rate (FAR) of simulated data 0.9850 and real data 0.6667	SL
[153]	UAV two modes: hovering and flying detection using radar	cadence–velocity diagram (CVD) with Pretained CNN AlexNet	Accuracy: hovering 95.1% and flying 96.6%	SL
[154]	3 types of UAV: hexacopter, helicopter, and quadcopter detection using radar	FMCW radar with NN3, SVM	Accuracy: NN3 of 90.18% and fusing multipath 95.73%	SL
[155]	2 types of UAV (Inspire 1 and F820) detection using radar	Pre-trained CNN (GoogLeNet)	Accuracy: air of 100% and anechoic chamber of 94.7%	SL, DTL
[156]	Mini-UAVs detection using radar	DNN	Accuracy gained of 98%	SL
[157]	Small and large-UAVs classification using radar	LSTM adaptive learning rate optimizing (ALRO)	Accuracy: 99.88%, Precision: 96.30%, recall: 95.52%, F1-score: 95.63%	SL
[158]	UAV detection using radar	SPDNet (Symmetric Positive Definite Network) type network similar to an MLP	Accuracy: 0.90	SL
[159]	UAV detection using ultra-wideband (UWB) radar	AlexNet with CNN structure	Accuracy: 95% or more	DTL
[160]	UAV detection using radar	Spectral correlation functions (SCFs) with Deep Belief Network (DBN)	Accuracy: above 90%	SSL
[161]	UAV detection using radar spectrogram images	radar spectrogram dataset with modified ResNet-18 called ResNet-SP model	Accuracy: above 83.39%	DTL
[162]	Mini-UAVs classification using radar	MDS with LSTM-RNN, Soft-max, GANomaly	Accuracy: LSTM-RNN of 89.0%, Softmax and GANomaly achieved area-under-curve (AUC) ranging 0.5 to 0.8	USL, SL
[163]	UAV movement classification using radar	AlexNet with CNN	Accuracy: 98%	DTL
[164]	UAV classification using radar	DopplerNet with CNN	Accuracy: 99.48%, Precision: 98.95%, Recall: 98.94%	SL
[165]	Multiple UAV classification using radar	continuous wave (CW) spectrogram with GoogLeNet	Accuracy: 99%	DTL
[166]	UAV classification using radar	YOLOv5s	Area under curve (AUC) of over 99%	SL
[167]	UAV classification using radar spectrograms obtained using an L-band staring radar	DT and CNN	Accuracy: DT and CNN of 93.33% and 97.22%	SL
[168]	UAV classification using radar	MDS with CNN	Accuracy: over 94.7%	SL
[169]	UAV detection using radar echo characteristics	MDS with DNN called MLP	Accuracy: probability of detection: 0.972, probability of a false alarm: 0.0034, and F1-score: 0.976	SL
[170]	UAV detection using radar signal	STFT with CNN	F1-score 0.816	SL
[171]	UAV detection and tracking using radar motion characteristics	Random forest model	Accuracy: 85.0%	SL
[172]	UAV classify using non-cooperative radar	LSTM-GRU, convolutional bidirectional-LSTM (CNN-BLSTM), CNN-BLSTM with attention (CNN-BLSTMA), CNN, CNN with attention (CNNA)	Accuracy: 0.9775, Precision: 0.9735 and recall: 0.9822, F1-score: 0.9777	SL
[173]	UAV detection using radar micro-Doppler signatures	CNN with FMCW	Accuracy: 78.68%	SL
[174]	UAV detection using radar time–frequency (T–F) signatures	Randomized (R-PCA) + SVM	Accuracy: 98.00%	SL
[175]	UAV detection using radar micro-Doppler signatures	Deep convolutional neural network (DCNN)	Accuracy: 97.4%	SL

[1] SL = supervised learning, DTL = deep transfer learning.

A non-cooperative UAV monitoring technique proposed in [146] utilized decision tree (DT) and SVM classifiers, along with the inclusion of MDS for UAV detection and classification. In the case of a two-class instance, the one-stage DT achieves a true positive (TP) ratio of 81.83% with a corresponding false positive (FP) ratio of 0.87%. The two-stage DT achieves 85.02% and 0.37% for TP and FP, respectively, using identical training and test datasets. The authors in [147] proposed an approach based on a radar device-based detection strategy to protect structures from UAV attacks. The real Doppler RAD-DAR (radar with digital array receiver) dataset was developed by the microwave and radar departments. Having a bandwidth of 500 MHz, the radar in operation operates on the 8.75 GHz base frequency range using frequency-modulated continuous wave technology. In the CNN-32DC, the suggested CNN exhibits variation in terms of the number of filters, combination layers, and the extraction of feature blocks. The selection process aimed to achieve the most accurate result, which was then compared to various ML and classification methods. The CNN-32DC demonstrates higher accuracy compared to similar networks while requiring less computation in terms of time.

Table 9. Datasets information of ML-based UAV classification and detection using radar data.

Reference	Datasets Information
[146]	Datasets included non-drones and drones with a total number of data points for training 208,982 and 4626, respectively. One- and two-stage models used total training data of 9252 (from 208,982) and 9244 (from 95,581).
[147]	Datasets taken from [164], where there are more than 17,000 samples of cars, people, and drones. The dimensions of input data were 11×61, and the dataset is divided into 70% training and 30% validation.
[148]	Three distinct datasets with varying sampling frequencies and signal durations t have been simulated. There were 160 samples in total in every radar return. 10000 complex-valued Gaussian noise signals of the same period t were included in each dataset, along with 2000 time series (samples) of each of the 5 drone classes.
[149]	A dataset named "DIAT-μ SAT" collected m-D signature T–F image samples, and here the total number of spectrogram images was $[6 \times 4849]$. More details of datasets can be found in the study in [176].
[150]	12 s data samples at 32 kHz were gathered for each position of every UAV in the two experiments. There were a total of 22,464 instances in the dataset for the short-distance and 18,144 instances for the long-distance experiment. Additionally, 2040 instances were derived from 120 s datasets with no tiny UAV. 70% and 30% of the total were made up of a training set and a testing set.
[151]	Datasets contained 700 MDS images per class, resulting in a total of 3500 MDS images. From total images, 80% used for training and 20% for validation.
[152]	Datasets were collected with a drone of DJI Phantom 3 and pulse-Doppler radar, height of about 15˜20 m, and detects a drone 2˜3 km away from the radar, pulse repetition frequency 6000 Hz, sampling rate 30 MHz frequency, and 86 frames of over 5000 R-D maps with size of 64×856 can be labeled and available for training and testing. A total of $11,000$ frames of simulated data were generated, and the training and testing data ratio was $4:1$.
[153]	Datasets contained using multistatic pulsed radar called NetRAD with DJI Phantom 4 Vision 2+ quadcopter drones. For the hovering class, a total of 18 recordings and 15 recordings for the flying class were produced.
[154]	Datasets contained 3 types of UAV: hexacopter, helicopter, and quadcopter, and 8 different vertical and horizontal positions are randomly selected to locate the drones. Thus, the total number of the signal segments was (3 drones)$\times$ (8 positions)$\times$(10 measurements)$\times$(6 segments) = 1440. The training set comprises 30% of all recordings, whereas the testing set consists of the remaining 70%.
[155]	The image data collection was created with 10,000 images from outdoors and 50,000 images from the anechoic chamber. A 256×256 pixel image was stored as the output size of the detected radar signal. The training and testing dataset in the ratio was $4:1$.
[156]	Datasets included 4 small drones and several birds; 2 model helicopters were used (Logo 400 or hkp01 and TREX 450 or hkp05). The total number of radar signal object sequences was 4310, of which 1051 belonged to the "hkp01" class, 871 to "hkp05", 1301 to "fpl08", 445 to "uav08", and 642 to the "bird" class.
[157]	The datasets collected from the study [177] constructed an anechoic chamber for RCS calculation and RCS measurement with frequency ranging from 26 to 40 GHz. More information on the number of drone datasets in this study is provided in [178].
[158]	The datasets of following drones were divided in 3 categories: fixedwing (EasyStar_ETS, Microjet_LisaM), rotorcraft (ardrone2, Bumblebee_Quad, LadyLisa, Quad_LisaMX, Quad_NavGo, bebop, bebop2), versatile (bixler), and others (birds) with total number of samples around $27,900$
[159]	Datasets contained 3 types of drones (Mavic pro, Phantom 3, Matrice 600) with a total of 6 drones. Training data included 50 frames of radar images (300 frames in total from all drones). The training data were used for 60% of the generated images and the remaining 40% used for testing.
[160]	Datasets contained 3 types of source (Bird, Cop, Drone). Training data included 70 data from each class and each set of testing data with 50 spectral correlation function (SCF) patterns.
[161]	The datasets included Metafly, Mavic Air 2, Disco, Walking, and Sit-Walking with the trained dataset of radar spectrogram for five low altitudes, slow speed, and small radar cross-section (LSS) targets being 2142, 2176, 2196, 2136, and 2112 with in total 10,762.
[162]	The datasets included the class of Air Trainer, Sky Walker, T-REX 550, QuadroXL, and OktoXL drones with simulated and measured training signals $506, 475, 956, 477, 480$ and $570, 886, 1284, 841, 1370$, respectively.
[163]	The dataset exhibited changes in elevation angle of 0 to 90 degrees at 1-degree step intervals and azimuth angle of 0 to 180 degrees at 5-degree step intervals. For every movement, a total of 6552 spectrogram images were created.
[164]	The database called RDRD [179] is composed of thousands of CSV files. The database contains 17485 samples in total, divided into three kinds of radar signals: 5720 cars, 6700 people, and 5065 drones, where 32.71% of the samples in the data correspond to cars, 28.97% to drones, and 38.32% to people.
[165]	The dataset was produced using a hexacopter (DJI S900) and two quadcopter (Joyance JT5L-404) drones. The characteristics of those drones' continuous wave (CW) spectrograms were acquired using coherent low-phase noise radar operating at 94 GHz.
[166]	The training dataset included 188 drone range-Doppler images, and the total number of images contained 376. The datasets were split as 60%, 20%, and 20% for training, validation, and testing.
[167]	In the whole dataset, there were 44 drone spectrograms, 5 car spectrograms, and 11 bird spectrograms. Each spectrogram had a set length of 80 frames, and an FFT with a length of 2048 was used; hence, each spectrogram represented roughly 20 seconds in time. The data were separated into training and testing with ratios of 60% and 40%.

Table 9. *Cont.*

Reference	Datasets Information
[168]	The dataset comprised five drones: the DJI S1000-A2, DJI Mavic Pro, DJI Phantom 4 Pro, Gryphon, and giant Spyder. The datasets displayed (from 483.8 to 484.1 seconds) belong to a random portion of a single trajectory. Trajectories taken on different days were included in the training and testing sets. The training set contains 36730 trajectory chunks, while the testing set contains 4670.
[169]	The dataset for UAV detection was constructed using a pulse-Doppler radar. Target locations, signal-to-noise ratios, and flying speeds have all been taken into account in the labeled radar dataset. The real measured dataset comprises 3135 data frames in total, of which 2508 are used for training and 627 are used for testing.
[170]	The datasets included 5 drones: Parrot Disco, Matrice 300 RTK, Mavic Air 2, Mavic Mini, and Phantom 4. For every combination of radar specification and SNR, a dataset was produced. Each dataset included 1000 spectrogram training samples that were distributed equally across the six classes (five drones and noise), and 350 examples were prepared for validation.
[171]	The training database contains sample amounts of 927, 635, and 1385 for birds, drones, and rain tracks, respectively. Accordingly, 217, 184, and 239 were the numbers for the testing database.
[172]	Four high-level intent classes were the focus of the datasets. The telemetry data used to create these classes were sourced from [180–183]. To create simulated radar data, the telemetry data [184] collected from GPS and inertial navigation system measurements were transformed. With fewer than 400 real drone flights, the telemetry data transformation was completed.

In [148], the authors proposed a CNN model with a DL foundation that incorporates MDSs, extensively employed in UAV detection applications. UAV radar returns and their associated micro-Doppler fingerprints are often complex-valued. However, CNNs typically neglect the phase component of these micro-Doppler signals, focusing solely on the magnitude. Yet, crucial information that could enhance the accuracy of UAV detection lies within this phase component. Therefore, this study introduced a unique complex-valued CNN that considers both the phase and magnitude components of radar returns. Furthermore, this research assessed the effectiveness of the proposed model using radar returns with varying sampling frequencies and durations. Additionally, a comparison was conducted regarding the model's performance in the presence of noise. The complex-valued CNN model suggested in this study demonstrated the highest detection precision, achieving an impressive 93.80% accuracy, at a sampling rate of 16,000 Hz and a duration of 0.01 s. This indicates that the suggested model can effectively identify UAVs even when they appear on the radar for very brief periods.

According to the study in [149], the authors proposed a novel lightweight DCNN model called "DIAT-RadSATNet" for precise identification and classification of small unmanned aerial vehicles (SUAVs) using the synthesis of micro-Doppler signals. The design and testing of DIAT-RadSATNet utilized an open-field, continuous-wave (CW) radar-based dataset of MDS recorded at 10 GHz. Equipped with 40 layers, 2.21 MB of memory, 0.59 G FLOPs, 0.45 million trainable parameters, and a calculation time complexity of 0.21 seconds, the DIAT-RadSATNet module was quite powerful. According to studies on unidentified open-field datasets, "DIAT-RadSATNet" achieved a detection/classification precision ranging between 97.1% and 97.3%, respectively.

In [150], the authors proposed a novel MDS-based approach, termed MDSUS, aimed at tackling the detection, classification, and localization (including angle of arrival calculation) of small UAVs. The synergistic utilization of a long short-term memory (LSTM) neural network and the empirical mode decomposition (EMD) methodology effectively addressed the blurring issue encountered in MDS within the low-frequency band. This approach enables the monitoring of small UAVs by leveraging attributes extracted from the MDS. In both short- and long-distance experiments, the LSTM neural network outperforms its two main rivals, namely CNN and SVM. Notably, precision is enhanced by 1.3% and 1.2% in the short- and long-distance experiments, respectively, when compared to the peak performance of the competing models, resulting in accuracies of 93.9% and 88.7%, respectively.

In [151], the authors employed a frequency-modulated continuous wave (FMCW) radar to generate a collection of micro-Doppler images, measuring dimensions of [3×3500]. These images corresponded to three different UAV models: DJI Inspire-1, DJI Inspire-2, and DJI Spark. Subsequently, the authors proposed a CNN architecture for the identification and categorization of these images. However, their research only encompassed one category class, and the maximum operational range of the targets was 412 meters. As a result, they were constrained in the number of available train/test samples for each class. In [152], the authors designed a three-layer CNN architecture for utilizing a generated micro-Doppler image collection of a DJI Phantom-3 UAV, which measured dimensions of [1× 11,000]. The time–frequency (T–F) images were captured using a pulse-Doppler radar operating in the X-band with a 20 MHz bandwidth. To ensure an adequate number of train/test samples for their study, the authors combined simulated and experimental data

The authors in [153] utilized a multistatic antenna array comprising one Tx/Rx and two Rx arrays to independently acquire matching MDS signatures, measuring [6 × 1036], while operating a DJI Phantom-vision 2+ UAV in two modes: hovering and flying. For categorization, they employed a pre-trained AlexNet model. In [154], the authors gathered a suitable MDS signature dataset of size [3 × 1440] using three different UAV types: hexacopter, helicopter, and quadcopter. The categorization of SUAV targets often involves employing the nearest neighbor with a three-sample (NN3) classifier. In [185], the authors investigated the feasibility of using a K-band CW radar to concurrently identify numerous UAVs. They used the cadence frequency spectrum as training data for a K-means classifier, which was derived from the cadence–velocity diagram (CVD) after transforming the time–frequency spectrogram. In their lab testing, they collected data for one, two, and all UAVs using a helicopter, a hexacopter, and a quadcopter. They found that the average precision outcomes for the categories of single UAVs, two UAVs, and three UAVs were 96.64%, 90.49%, and 97.8%, respectively.

In order to categorize two UAVs (Inspire 1 and F820), in [155], the authors examined the pre-trained CNN (GoogLeNet) for UAV detection. The MDS was measured, and its CVD was ascertained while in the air at two altitudes (50 and 100 meters) over a Ku-band FMCW radar. The term 'merged Doppler image' (MDI) refers to the combination of the MDS and CVD pictures into a single image. Ten thousand images from measurements conducted outside were created and fed into the CNN classifier using fourfold cross-validation. The findings indicate that 100% accuracy in classifying the UAVs was possible. Remarkably, trials conducted indoors in an anechoic environment showed worse categorization ability.

The authors in [186] proposed a UAV detection and classification system utilizing sensor fusion, incorporating optical images, radar range-Doppler maps, and audio spectrograms. The fusion features were trained using three pre-trained CNN models: GoogLeNet, ResNet-101, and DenseNet-201, respectively. During training, the parameters, including the number of epochs, were set to 40, and the learning rate was set to 0.0001. The classification F1-score accuracies of the three models were 95.1%, 95.3%, and 95.4%, respectively.

Using mmWave FMCW radar, the authors in [187] described a unique approach to UAV location and activity classification. The suggested technique used vertically aligned radar antennae to measure the UAV elevation angle of arrival from the base station. The calculated elevation angle of arrival and the observed radial range were used to determine the height of the UAV and its horizontal distance from the ground-based radar station. ML techniques were applied to classify the UAV behavior based on MDS that was retrieved from outdoor radar readings. Numerous lightweight classification models were examined to evaluate efficiency, including logistic regression, SVM, light gradient boosting machine (GBM), and a proprietary lightweight CNN. The results showed that 93% accuracy was achieved with Light GBM, SVM, and logistic regression. A 95% accuracy rate in activity categorization was also possible with the customized lightweight CNN. Pre-trained models (VGG16, VGG19, ResNet50, ResNet101, and InceptionResNet) and the suggested lightweight CNN's efficiency were also contrasted.

In [188], the author introduced the inception-residual neural network (IRNN) for target classification using MDS radar image data. By adjusting the hyperparameters, the suggested IRNN technique was examined to find a balance between accuracy and computational overhead. Based on experimental findings using the real Doppler radar with digital array receiver (RAD-DAR) database, the proposed method can identify UAVs with up to 99.5% accuracy. Additionally, in [189], the authors proposed employing a CNN to detect UAVs using data from radar images. The microwave and radar group developed the real Doppler RAD-DAR radar technology, a range-Doppler system. They built and evaluated the CNN by adjusting its hyperparameters using the RAD-DAR dataset. The highest accuracy in terms of time was achieved when the number of filters was set to 32, as per the experimental findings. With an accuracy of 97.63%, the network outperformed similar image classifiers. The research team also conducted an ablation investigation to examine and confirm the significance of individual neural network components.

The authors addressed the issue of UAV detection using RCS fingerprinting in their study [190]. They conducted analyses on the RCS of six commercial UAVs in a chamber with anechoic conditions. The RCS data were gathered for both vertical–vertical and horizontal–horizontal polarizations at frequencies of 15 GHz and 25 GHz. Fifteen distinct classification algorithms were employed, falling into three categories: statistical learning (STL), ML, and DL. These algorithms were trained using the RCS signatures. The analysis demonstrated that, while the precision of all the techniques for classification was improved with SNR, the ML algorithm outperformed the STL and DL methods in terms of efficiency. For instance, using the 15 GHz VV-polarized RCS data from the UAVs, the classification tree ML model achieved an accuracy of 98.66% at 3dB SNR. Monte Carlo analysis was employed, along with boxplots, confusion matrices, and classification plots, to assess the efficiency of the classification. Overall, the discriminant analysis ML model and the statistical models proposed by Peter Swerling exhibited superior accuracy compared to the other algorithms. The study revealed that both the ML and STL algorithms outperformed the DL methods (such as Squeezenet, GoogLeNet, Nasnet, and Resnet-101) in terms of classification accuracy. Additionally, an analysis of processing times was conducted for each program. Despite acceptable classification accuracy, the study found that the STL algorithms required comparatively longer processing times than the ML and DL techniques. The investigation also revealed that the classification tree yielded the fastest results, with an average classification time of approximately 0.46 milliseconds.

A UAV classification technique for polarimetric radar, based on CNN and image processing techniques, was presented by the authors in [191]. The suggested approach increases the accuracy of drone categorization when the aspect angle MDS is extremely poor. They suggested a unique picture framework for three-channel image classification CNN in order to make use of the obtained polarimetric data. An image processing approach and framework were presented to secure good classification accuracy while reducing the quantity of data from four distinct polarizations. The dataset was produced using a polarimetric Ku-band FMCW radar system for three different types of drones. For quick assessment, the suggested approach was put to the test and confirmed in an anechoic chamber setting. GoogLeNet, a well-known CNN structure, was employed to assess the impact of the suggested radar preprocessing. The outcome showed that, compared to a single polarized micro-Doppler picture, the suggested strategy raised precision from 89.9% to 99.8%.

2.4.1. Challenges and Solutions of Radar-Based UAV Detection and Classification Using ML

- **Signal processing complexity:** Radar signals can be complex due to noise, clutter, and interference, requiring sophisticated signal processing techniques. Develop advanced signal processing algorithms to filter noise, suppress clutter, and enhance signal-to-noise ratio for accurate detection.
- **Signal ambiguity and multipath effects:** Signal ambiguity arising from multiple reflections (multipath effects) in radar signals, impacting accurate target localization and classification. Explore waveform design and beamforming strategies to mitigate multipath effects and improve spatial resolution.
- **Classification from radar signatures:** Accurately classifying different UAV types based on radar signatures exhibiting similar characteristics. Utilize machine learning

models capable of distinguishing subtle radar signal variations for precise classification, potentially leveraging ensemble learning techniques.

- **Real-time processing and computational complexity:** Processing radar data in real time while managing computational complexity for timely detection and response. Optimize machine learning algorithms and hardware configurations for efficient real-time processing, potentially utilizing parallel computing or hardware acceleration.
- **Adverse weather conditions:** Performance degradation in adverse weather conditions (e.g., rain or fog) affects radar signal quality and detection accuracy. Develop adaptive algorithms capable of compensating for weather-induced signal degradation and maintaining robust detection capabilities.
- **Security and interference mitigation:** Vulnerability to interference and potential security threats in radar-based systems. Implement interference mitigation techniques and security measures (e.g., encryption and authentication) to safeguard radar signals and system integrity.

2.4.2. Future Directions of Radar-Based UAV Detection and Classification Using ML

- **Multisensor fusion and integration:** Integration of radar data with other sensor modalities (e.g., visual or acoustic) for improved detection accuracy and robustness [107].
- **Advanced machine learning techniques:** Exploration of advanced machine learning methods (e.g., reinforcement learning or meta-learning) for adaptive radar-based UAV detection systems [192].
- **Enhanced model interpretability:** Development of interpretable machine learning models for radar-based UAV detection to enhance transparency and trust in decision-making [193].
- **Standardization and collaboration:** Collaboration among researchers, industries, and regulatory bodies for standardizing radar-based UAV detection systems, ensuring interoperability, and advancing research in this field [194].

In [195], the authors proposed a novel UAV classification technique that integrates DL into the classification process, specifically designed to handle data from surveillance radar. To differentiate between UAVs and undesirable samples like birds or noise, a DNN model was employed. The conducted studies demonstrated the effectiveness of this approach, achieving a maximum classification precision of 95.0%.

The authors in [173] proposed a unique approach to data augmentation based on a deterministic model, which eliminates the need for measurement data and creates a simulated radar MDS dataset suitable for UAV target categorization. Improved prediction performance is achieved by training a DNN on appropriately generated model-based data. A 77-GHz FMCW automotive radar system was used to classify the number of UAV motors into two groups, and the results were summarized. This demonstrated the effectiveness of the suggested methodology: a CNN trained on the synthetic dataset achieved a classification precision of 78.68%, while a standard signal processing data augmentation method on a limited measured dataset resulted in a precision of 66.18%.

2.5. Reinforcement Learning-Based Approach

In reinforcement learning (RL), an agent interacts with the environment and takes some action. Based on the action, the agent receives a reward by evaluating the action taken by the agent. This approach learns an optimal policy by trial and error to solve a problem in the real world [196]. Deep reinforcement learning (DRL) has been widely adopted to solve problems in different fields of science and engineering. Previous drone-related studies are mainly focused on path planning, navigation control, and communication coverage [197]. Some of the previous studies have considered drone detection approaches as intrusion detection. The study conducted in [198] proposed an intrusion detection system by using a Markov decision process optimization problem via the RL approach. The RL-based approach was implemented in [199] regarding counter-drone technology to provide a safeguarded sky while not clashing the other objects in the neighborhood. Image depth is considered for RL input and other scalar parameters like velocities, distance of the target, and elevation angle. Another RL-based study was conducted in [200]; first, the drone is detected by the YOLOv2 algorithm, and the drone is then tracked. The RL approach is used by the follower drone to predict the action of the intruder/target drone by using image frames. Later, a deep object detector and search area proposal algorithm are used to predict target drones. Another study in [201] proposed a deep Q-network-based method to counter drones in 3D space. The authors used EfficientNet-B0, a sub-version of EiffientNet, to detect drones that can capture small objects. Nine models were proposed for countering drone objects in 3D space, among which Model-1 and Model-2 were chosen as the best models based on their training and testing performance. RL-based studies are partially used in drone detection and classification for drone data. However, future research can be focused on the classification and detection of drones by properly setting the RL environment.

2.6. UAV Classification Using Hybrid Methods

Despite the above-discussed four general detection classification methods, there is another possible detection method called hybrid sensor-based detection. The hybrid method is more dependable, durable, and personalized for drone detection techniques in various situations. Using visible light or optical detection in conjunction with acoustic, RF, and radar detection is a common trend in hybrid detection. Utilizing the combined outputs of two sensing technologies to make a detection judgment is a more popular method of hybrid detection. An alternate method is to generate an early detection alarm using a long-range non-line-of-sight detection scheme (such as acoustic, RF, or radar) and then use the alarm's output to trigger the second sensor (usually a camera) to change its configurations (such as direction, zoom level, etc.) to perform a more precise and reliable identification. The hybrid detection scheme of UAVs based on ML and DL is shown in Figure 7a,b. In addition, the summary of related work based on a hybrid detection scheme using ML is shown in Table 10. Moreover, the dataset information of ML-based UAV classification and detection using hybrid sensor data is shown in Table 11. Recently, many works have been completed using hybrid sensors UAV detection and classification based on ML algorithms [69,202–206].

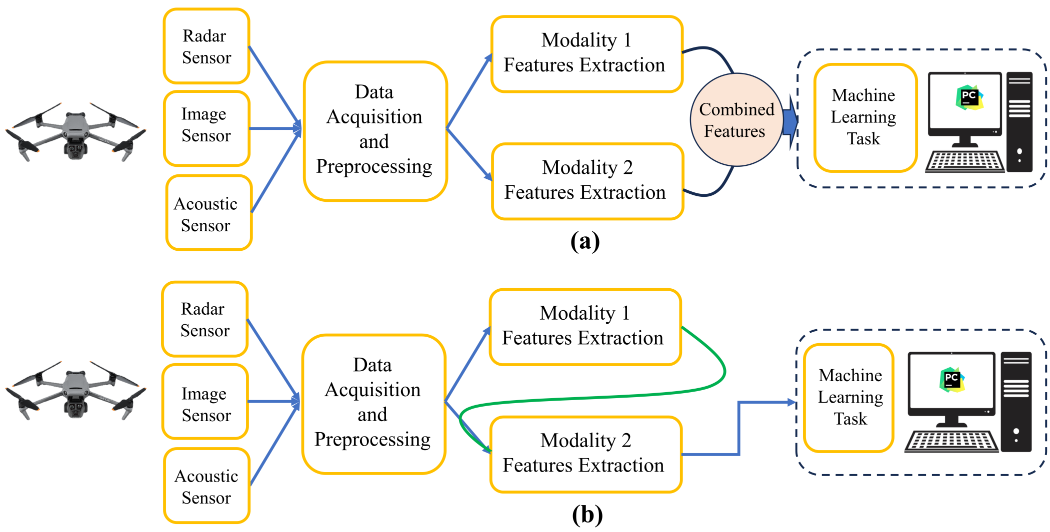

Figure 7. The overview of the machine learning classification of hybrid sensor detection: (**a**) fusion of sensor using compressed multisensor features to input into single detection and classification system; (**b**) detection decisions using combined sensor fusion system.

Table 10. Comparison summary of ML-based UAV classification and detection using hybrid sensor data.

Reference	Detection Target	Machine Learning Method	Performance	Model Types [1]
[69]	UAV detection using sensor fusion	CNN and DNN	Precision: 79%, Recall: 78%, F1-score: 77%	SL
[202]	UAV detection using multisensor	GMM and YOLOv2	For Infrared sensor, Precision: 89.85%, Recall: 87.06%, F1-score: 88.44%, For Visible camera, Precision: 86.95%, Recall: 86.68%, F1-score: 86.82%, For Audio sensor, Precision: 93.54%, Recall: 92.93%, F1-score: 93.23%	SL
[203]	UAV detection using thermal imaging, vision, and 2D radar sensor	MLP	The system acquired detection accuracy of visual and audio were 79.54% and 95.74%, respectively	SL
[205]	UAV detection using visual and acoustic sensor	MFCC with SVM	The system gained of precision, recall, and F1-score were 99%, 100%, and 95% for UAV detection	SL
[206]	UAVs detection using radar and camera sensor	MDS with IMM filters and RNN, YOLOv5	Accuracy gained of 98%	SL
[207]	UAV detection using image and audio data	YOLOv5	Accuracy: 92.53%	SL
[186]	UAV detection using sensor fusion	CNN assisted GoogLeNet, ResNet-101, DenseNet-201	F1-score of (GoogLeNet = 95.1%, ResNet-101 = 95.3%, DenseNet-201 = 95.4%)	SL

[1] SL = supervised learning.

Table 11. Datasets information of ML-based UAV classification and detection using hybrid sensor data.

Reference	Datasets Infomation
[69]	Datasets combined RF and images, where RF data were taken from [57] and the combination of image and RF datasets was 80 samples; this size is extremely small. Created huge datasets later and made more than 5000 images using 1500 images.
[202]	The datasets consist of 90 audio clips, 650 videos (365 in infrared and 285 visible, each running 10 seconds), and 203,328 annotated images. The visible video resolution was 640 × 512 pixels, while the infrared video was 320 × 256 pixels. The maximum sensor-to-target distance for a drone was 200m. Datasets found in [208].
[203]	Dataset consists of 20 sets of images and sound clips. Moreover, 3 audio streams and 30 image streams were included in each data collection. The image sequence has a frame rate of 25 FPS and a resolution of 1920 × 1080. The audio sampling rate was 48 kHz. Selected 90% of the data for training and 10% testing.
[205]	The result of 15 UAV flight recordings was the dataset. There were 2195 features in the UAV class and 2195 features in the non-UAV class obtained from the training set, and 432 features in each class were obtained from the test set.
[206]	Radar dataset includes radar tracks for 1224 different ground targets (cars, people), 1369 birds, and 9138 UAVs. The sampling rate was 10 samples/s. For optical, around 85 videos totaling 207,663 frames were gathered; of these, 154,089 had a UAV, 5200 had an OFO (other flying object), and 48745 were background frames devoid of any objects.
[207]	Pitch shifting was employed for data augmentation for acoustic features, and 4220 samples were used for training, 1200 samples were used for validation, and 308 samples were used for testing.

The authors in [69] presented a detection system based on ANNs. This system processed image data using a CNN and RF data using a DNN. A single prediction score for drone presence was produced by concatenating the characteristics of the CNNs and DNNs and then feeding them into another DNN. The feasibility of a hybrid sensing-based approach for UAV identification was demonstrated by the numerical results of the proposed model, which achieved a validation accuracy of 75%.

The study [202] thoroughly described the process of developing and implementing an automated multisensor UAV detection system (MSDDS) that utilizes thermal and auditory sensors. The authors augmented the standard video and audio sensors with a thermal infrared camera. They also discussed the constraints and potential of employing GMM and YOLOv2 ML approaches in developing and implementing the MSDDS method. Furthermore, the authors assembled a collection of 650 visible and infrared videos featuring helicopters, airplanes, and UAVs. The visible videos have a resolution of 640 × 512 pixels, while the infrared videos are scaled to 320 × 256 pixels. The authors focused their analysis on evaluating the system's efficiency in terms of F1-score, recall, and accuracy.

The authors of [203] presented a system that continuously monitors a certain region and produces audio and video feeds. The setup consisted of thirty cameras (visual sensors) and three microphones (acoustic sensors). Following this, features were extracted from the audio and video streams and sent to a classifier for detection. For the classification and training of the datasets, they employed the popular SVM-based ML algorithm. The efficiency of the visual detection approach was 79.54%, while the audio-assisted method outperformed it significantly at 95.74%, as indicated by the findings.

A method for detecting tiny UAVs, which utilizes radar and audio sensors, was presented by the authors in [204]. The system employs a customized radar called the "Cantenna" to detect moving objects within a specified target region. An acoustic sensor array is utilized to discern whether the object identified by the radar is a UAV. Furthermore, the system incorporates a pre-trained DL model consisting of three MLP classifiers that collectively vote based on auditory data to determine the presence or absence of a UAV. When the system was evaluated using both field and collected data, it demonstrated accurate identification of every instance in which a UAV was present, with very few false positives and no false negatives.

The authors in [205] introduced a multimodal DL technique for combining and filtering data from many unimodal UAV detection techniques. To conduct UAV identification predictions, they used a combined set of data from three modalities. Specifically, an MLP network was utilized to combine data from thermal imaging, vision, and 2D radar in the form of range profile matrix data. To enhance the accuracy of deductions by combining characteristics collected from unimodal modules, they provided a generic fusion NN architecture. Multimodal features from both positive UAV and negative UAV detections make up the training set. The system achieved precision, recall, and F1-scores of 99%, 100%, and 95%, respectively.

The authors in [206] proposed a combined classification structure based on radar and camera fusion. The camera network extracts the deep and complex characteristics from the image, while the radar network collects the spatiotemporal data from the radar record. Several field tests at various periods of the year were used to establish synchronized radar and camera data. The field dataset was used to evaluate the performance of the combined joint classification network, which incorporates camera detection and classification using YOLOv5, as well as radar classification using a combination of interacting multiple model (IMM)) filters and RNN. The study's results demonstrated a significant enhancement in classification accuracy, with birds and UAVs achieving 98% and 94% accuracy, respectively.

The authors in [143] introduced a multisensory detection technique for locating and gathering information on UAVs operating in prohibited areas. This technique employed a variety of methods, including video processing, IR imaging, radar, light detection and ranging (LIDAR), audio pattern evaluation, radio signal analysis, and video synthesis. They proposed a set of low-volume neural networks capable of parallel classification, which they termed concurrent neural networks. This research focused on the detection and classification of UAVs using two CNNs: a self-organizing map (SOM) for identifying objects in a video stream and a multilayer perception (MLP) network for auditory pattern detection.

2.6.1. Challenges and Solutions of Hybrid Sensor-Based UAV Detection and Classification Using ML

- **Sensor data fusion and integration:** Integrating heterogeneous data from various sensors (e.g., radar, visual, and acoustic) with different characteristics, resolutions, and modalities. Develop fusion techniques that align and synchronize data from multiple sensors for holistic UAV detection and classification.
- **Data synchronization and alignment:** Aligning data streams from diverse sensors in real time for accurate fusion and analysis. Implement synchronization methods to align temporal and spatial information from different sensors for cohesive fusion.

- **Complexity in feature fusion:** Fusion of diverse features extracted from various sensor modalities for meaningful representation. Investigate advanced feature fusion techniques to combine and extract relevant information from heterogeneous sensor data for robust classification.
- **Model complexity and computational cost:** Developing complex machine learning models for fusion sensor-based classification that can be computationally expensive. Explore model optimization techniques and efficient algorithms to handle the computational burden without compromising accuracy.
- **Scalability and real-time processing:** Scaling fusion sensor-based systems to handle real-time processing of large volumes of data. Optimize hardware configurations and leverage parallel processing to enable real-time analysis of fused sensor data.

2.6.2. Future Directions of Hybrid Sensor-Based UAV Detection and Classification Using ML

- **Deep learning and fusion models:** Advancing deep learning architectures tailored for sensor fusion to leverage the strengths of multiple sensor modalities for UAV detection and classification [30,69].
- **Dynamic fusion strategies:** Developing adaptive fusion strategies capable of dynamically adjusting sensor weights or modalities based on environmental conditions for improved classification accuracy [209,210].
- **Privacy-preserving fusion techniques:** Addressing privacy concerns by designing fusion techniques that preserve privacy while maintaining high accuracy in UAV detection [211,212].
- **Standardization and interoperability:** Collaborating across industries to establish standardized protocols for sensor data fusion, ensuring interoperability and compatibility among different sensor systems [72,213].

3. Conclusions and Discussion

In this survey study, ML-aided UAV detection and classification using some of the latest technologies, such as (1) RF-based UAV detection, (2) visual data (images/video)-based UAV detection, (3) acoustic/sound-based UAV detection, and finally (4) radar-based UAV detection, were extensively reviewed. In addition, this survey suggests potential challenges, solutions, and possible future directions of each detection technique described. Research on the enhancement of detection accuracy for UAVs is challenging for the four mentioned detection techniques adopted by traditional algorithms. The overview of ML-based UAV detection and classification depends on the experimental comparison of different models with the highest accuracy, as presented in Table 12. It requires current powerful methods (DL and ML) for incrementally identifying performance automatically.

Table 12. Experimental comparison of different models with the highest accuracy.

Data Collection Technique	Models and Reference	Accuracy	Dataset	Loss Function	Special Feature
RF signal	DNN/CNN [42]	100 %	DroneRF Dataset [47]	MSE/Cross-entropy	Compressive sensing-based data extraction.
RF signal	CNN, LR, KNN [34]	100%	SDR Dataset [47]	Unspecified	Different deep learning architecture is used for drone detection and identification.
RF signal	CNN [47]	99.7%	DroneRF Dataset [47]	MSE	Bluetooth and Wi-Fi signals are extracted for UAV detection.
Visual data	CNN [80]	98.7%	Aerial vehicle, Drone vs. Bird Detection, Anti-UAV [90,214,215]	Customized loss function used	Four methods have been evaluated to make baseline for UAV detection.
Visual data	YOLOv5 [88]	96.7%	Kaggle [93]	Adam	Image processing phase was performed before training.

Table 12. *Cont.*

Data Collection Technique	Models and Reference	Accuracy	Dataset	Loss Function	Special Feature
Visual data	CNN, SVM, NN [76]	93%	Authors' dataset	Not specified	Differentiate between drone and bird.
Acoustic data	SVM [124]	99.9%	Publicly available dataset	Different SVM kernels used	Five acoustic features were considered for classification.
Acoustic data	SVM,GNB, KNN, and NN [131]	99.7%	Authors' dataset	Different parameters are used for different models	Feature extraction settings altered in order to maximize performance.
Acoustic data	Lightweight CNN and SVM [113]	98.78%	Sound effect database	For Adam, SVM liner, Gaussian, and Cubic, kernel is used	Two different models are added to increase accuracy.
Radar data	CNN (GoogLeNet) [155]	100%	Authors' dataset	RMSprop	Micro-Doppler signature is used for training data.
Radar data	CNN [164]	99.48%	RDRD databse	Adam	Reduce the false alarm
Radar data	CNN (GoogLeNet) [165]	99%	micro-Doppler spectrogram images	RMSprop	Continuous wave spectrogram features of different drones obtained with low phase noise investigated.

Indeed, highlighting the key areas of development in RF-based UAV detection, visual data (images/video)-based UAV detection, acoustic/sound-based UAV detection, and radar-based UAV detection will provide a comprehensive view of advancements in UAV detection technologies.

One of the most widely used anti-UAV techniques is the RF-based UAV identification framework, which utilizes the RF characteristics of UAVs to identify and categorize them [75]. The aspects of emphasis regarding RF-based UAV detection are as follows: advancements in RF signal processing techniques for improved detection accuracy; development of machine learning algorithms to analyze and classify RF signatures of UAVs; enhancement of multisensor fusion for combining RF data with other modalities for better detection in complex environments; and research on countermeasures for RF-based detection evasion techniques employed by UAVs.

Computer vision or visual techniques can be employed to identify UAVs without RF transmission capabilities by utilizing inexpensive camera sensors. These sensors offer the advantage of providing additional visual data, including the UAV model, dimensions, and payload, which traditional UAV detection systems cannot deliver. The aspects of emphasis regarding visual-based UAV detection are as follows: integration of deep learning models for object detection and recognition in UAV imagery; improvement in real-time processing capabilities for quick and accurate UAV identification; exploration of computer vision algorithms to handle various environmental conditions and challenges, such as low light or adverse weather; and research on the development of robust algorithms to differentiate between UAVs and other objects in the visual spectrum.

Even in low-visibility situations, very inexpensive acoustic detection systems categorize certain UAV rotor audio patterns using a variety of auditory sensors or microphones [17]. The aspects of emphasis regarding acoustic-based UAV detection are as follows: advancements in sensor technologies for capturing and processing acoustic signals associated with UAVs; integration of machine learning and pattern recognition techniques to identify unique acoustic signatures of UAVs; research on mitigating challenges such as background noise and signal interference; and exploration of distributed sensor networks for triangulation and improved localization of UAVs using acoustic cues.

Radar is a conventional sensor that can reliably identify objects in the sky over extended distances and is nearly unaffected by adverse weather and light [30,216]. The aspects of emphasis regarding radar-based UAV detection are as follows: development of radar systems with enhanced sensitivity and resolution for UAV detection; integration of machine learning algorithms to analyze radar returns and distinguish UAVs from other objects; exploration of radar waveform diversity to improve detection performance in different scenarios; and research on the development of radar-based tracking systems for continuous monitoring and prediction of UAV movements. By emphasizing these specific areas within each detection method, the development of UAV detection systems can be more targeted and effective. This approach ensures a comprehensive and nuanced understanding of the challenges and opportunities within each domain.

The goal of data fusion, or hybridizing sensory data from numerous sensors, is to integrate information from various modalities to draw conclusions that would be unattainable with just one sensor. Domains such as target surveillance and identification, traffic management, UAV detection, remote sensing, road barrier detection, air pollution sensing, complex equipment monitoring, robotics, biometric applications, and smart buildings all benefit from this technique. Multisensor data fusion enables the identification of trends, the extraction of insights, and the establishment of correlations between diverse sensor types thanks to the wealth of information available in the real world. While multisensor fusion is a viable strategy, designing systems to meet specific use cases requires thorough research and experimental validation. The main drawbacks of sensor fusion include increased deployment costs, computational complexity, and system intricacy. Synchronization and latency issues may arise when integrating multiple sensors for joint detection. The recent surge in the development of AI and DNNs has garnered significant attention for their ability to represent multimodal data and address the challenges posed by hybrid sensor detection scenarios [217]. Despite the above technologies of UAV detection, spectral [218] and multispectral remote sensing imagery [219]-based techniques can be another research scope for precision UAV classification and detection. In the context of spectral imagery, it can be explored in the use of advanced spectral–spatial feature extraction methods, which can enhance accuracy regarding the discriminative power of detection models.

In order to keep abreast of the most recent progress in UAV development and research trends, researchers, developers, and practitioners might benefit greatly from consulting this review article. This work adds invaluable insights for future research and development in this dynamic field of UAVs, offering a thorough analysis that contributes significantly to the scientific literature on DL- and ML-based UAV detection and classification technologies.

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