Received August 8, 2019, accepted August 29, 2019, date of publication September 23, 2019, date of current version October 4, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2942944

Machine Learning-Based Drone Detection and Classification: State-of-the-Art in Research

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ABSTRACT This paper presents a comprehensive review of current literature on drone detection and classification using machine learning with different modalities. This research area has emerged in the last few years due to the rapid development of commercial and recreational drones and the associated risk to airspace safety. Addressed technologies encompass radar, visual, acoustic, and radio-frequency sensing systems. The general finding of this study demonstrates that machine learning-based classification of drones seems to be promising with many successful individual contributions. However, most of the performed research is experimental and the outcomes from different papers can hardly be compared. A general requirement-driven specification for the problem of drone detection and classification is still missing as well as reference datasets which would help in evaluating different solutions.

INDEX TERMS Drone detection, drone classification, machine learning, radar, vision, acoustics, radio-frequency.

I. INTRODUCTION

Despite attracting a wide attention in diverse civil and commercial applications, Unmanned Air Vehicles (UAVs - also known as drones) undoubtedly pose a number of threats to airspace safety that may endanger people and property. While such threats can be highly diverse in terms of the attackers' intentions and sophistication, ranging from pilot unskillfulness to deliberate attacks, they all can produce severe disruption. Their frequency is also on the increase: in the first few months of the year 2019, for example, various airports in the USA, UK, Ireland, and UAE have experienced major disturbance of operation following drone sightings [1]. Classic risk theory tells us that hazards whose probability is high and whose consequences are severe generate huge risks (risk assessment = probability × impact). Flight authorities worldwide are working hard on reducing the probability aspect of the risk equation by regulating drone operation. Regulations may discourage careless or unskilled drone operation, but cannot prevent criminal or terroristic attacks. To be effective, they must be supported by technologies enabling **i-** drone detection, classification, and tracking, **ii-** drone interdiction, and **iii-** evidence collection in the case of violation. In addition to these technologies which essentially address uncooperative drones, friendly UAVs should have onboard preventive technologies to support safe operation such as sense&avoid, geofencing, parachuting systems, as well as mechanisms against different attacks such as jamming or hijacking of the control signal. Figure 1 classifies the technologies which were deployed to support safe drone operations into four main categories with examples.

This paper addresses the detection and classification technologies specifically those which are based on machine learning (ML). Due to its ability to recognize patterns without a man-in-the-loop, ML has shown major advantages in object detection and classification in diverse areas. Limiting the reliance on man-in-the-loop is desired not only because of human inability to recognize far or small objects and the risk of reduced attention due to fatigue or boredom. Rather, ML can perform pattern recognition using modalities, which cannot be perceived by humans altogether. These include radio frequencies as well as optic and acoustic signals beyond the abilities of human sense organs.

Recently, many technical papers have provided short reviews of related work on drone detection [2], [3]. Also, some review articles have appeared which consider single or multiple modalities [4], [5]. Most, if not all of these reviews, however, are focused on the functional level of the

The associate editor coordinating the review of this manuscript and approving it for publication was Kemal Polat.

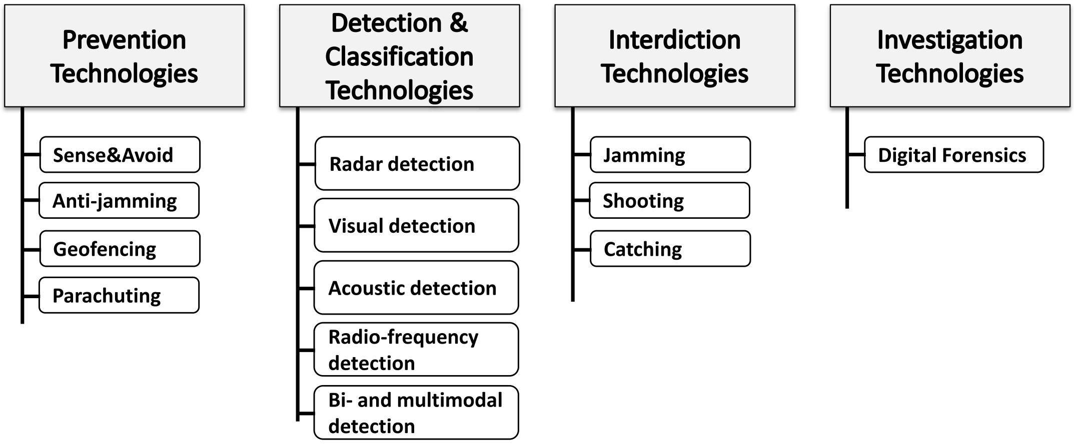

FIGURE 1. Different technologies applied to support safe drone operations.

TABLE 1. Comparison of advantages and disadvantages of different drone detection technologies [4].

Detection Technology	Advantages	Disadvantages
Radar	Low-cost Frequency-Modulated Continuous Wave (FMCW) radars are resistant to fog, cloud, and dust as opposite to visual detection; and less pron to noise as opposite to acoustic detection. Radar does not require a line-of-sight (LOS). Higher frequency radars such as mmWave radars offer higher resolution in range and enable capturing micro-Doppler signature (MDS).	Drones have small radar cross sections (RCS) which makes the detection more demanding. mmWave has higher path loss, which limits drone detection range.
Acoustic	Does not require a LOS, so it works in low-visibility environments. Low-cost depending on the employed microphone arrays	Sensitive to ambient noise especially in loud areas. Wind condition affects detection performance. Requires a database of acoustic signature for different drones for training and testing.
Visual	Low-cost depending on the utilized cameras and optical sensors or reusing existing surveillance cameras. Human assessment of detection results using screens is easier than other modalities	Level of visibility is affected by dust, fog, cloud, and day time. High-cost thermal, laser-based, and wide field-of-view cameras may be required. LOS is necessary.
Radio-frequency (RF) signal-based detection	Low-cost RF-sensors. No LOS is required. Long detection range.	Not suitable for detecting drones flying autonomously without any communication channels. It requires training to learn RF signal signatures.

different technologies and limit the evaluation to comparing their general advantages and disadvantages as summarized in Table 1.

To support researchers in this area as well as interested parties including drone manufacturers, drone operators, anti-drone system operators, regulators, and law enforcement, this paper provides a wide and deep look into state-of-the-art contributions in the field of drone detection and classification using machine learning. For this purpose, we followed a systematic approach by addressing each of the following questions for each reviewed paper.

What is the classification objective?

Classification is an application of supervised ML where all data samples used in the training and testing are labeled. The number of different labels used in annotating the dataset is equal to the number of classes. Using machine learning to *detect* a drone is a binary classification problem where two labels are used, e.g., "Drone" and "No Drone". Recognizing drones from birds or drones from other aircrafts is also a binary classification problem with corresponding labels for the data. Several researchers tried to identify the drone type by ML-classification. In this case we refer to multi-class classification with as many classes and labels as the number of identifiable drone types. Multi-class classification was also used to specify the drone itself, e.g., by determining the number of its rotors, or estimating its payload.

What dataset is used?

Machine learning is about learning from data. Both the quality and quantity of data used in training and testing are vital for learning powerful classification models, with low bias and variance. To reduce the bias in the learned model (under-fitting effect), the data should cover a wide range of cases which stem from or resemble real situations. To reduce the variance (prevent over-fitting), the model should learn from a large amount of data to gain enough experience and increase its generalization capability. In the field of drone classification, there are still no widely recognized reference datasets for the different modalities. In most, if not all cases, researchers generated their own data using different ways including simulations, experiments in lab, as well as outdoor measurements. In some cases, data generated in the lab, e.g., acoustic data are mixed with noise to emulate a real environment.

Which features are extracted?

In general, raw sensor data requires some pre-processing before they are fed to the ML process. This include filtering to suppress noise and clutter or implementing principle component analysis (PCA) or independent component analysis (ICA) to reduce the data dimensionality. Feature engineering and selection is an essential but difficult task in most ML algorithms to ensure learning efficient and generate useful models. In the literature on drone classification, researchers made use of different features in the time and frequency domains depending on the used modalities. Feature extraction and selection is omitted when deep learning is employed since this ML scheme learns features inherently, however, at the cost of complexity and higher demand of data.

What classifiers are employed?

Machine learning packages are widely available nowadays and it is a common practice to try different classifiers and compare their performance. This is a typical scenario in ML because it is still hard to tell from the beginning which classifier would work better on which features especially in new areas such as drone detection. Researchers in the related work tried multiple classifiers including support vector machines (SVM), artificial neural networks (ANN), random forests, etc.

Which results are reported?

The quality of classification models is generally measured by the classification accuracy which boils down to the number of correct predictions from all predictions made. Cross validation is a widely used technique to improve the quality of the classification model especially if limited data are available. Trained models can also be tested and verified using real unseen data. For drone classification, researchers essentially utilized classification accuracy to estimate the classification performance. Depending on the risk level associated with drone flights, classification accuracy may not be sufficient for evaluating the performance of a classification model. In such cases, model precision should be considered to reduce the percentage of false negatives.

The rest of the paper is divided into five sections. The next four ones review the ML-based drone classification technologies for each modality from the most to the least popular ones. Each of these sections has three main parts: a detailed review of the papers, an overview table, and a discussion. The last section gives a general summary for all technologies, provides some research directions for the future, and concludes the paper.

II. ML-BASED DRONE CLASSIFICATION BY RADAR

Researchers who applied ML to radar signals followed one of the following objectives (see Table 2):

A. Drone detection: This applies when two labels are used to annotate data: drone vs. no-drone.
B. Classification of drones vs. birds: In this case, two labels are used: drone vs. bird.
C. Classification of drones vs. drones: This applies when as many labels are used as the number of investigated drone types.
D. Drone characterization classification: This is the case when the data is labeled according to a value of a specific drone characteristic such as the payload or the number of rotors.
E. Multi-drone detection: In this case, researchers labeled the data with the number of drones flying simultaneously.

The following subsections are structured according to these classification objectives.

A. DRONE DETECTION

Jahangir and Baker showed how the need for ML arises in the context of radar detection in practice [6]. The authors used a high-end 3-D holographic radar with a transmission power of 10kW and 32×8 receiver array to detect a drone at a reasonable range of around 1km. Employing the radar standard configuration, the detection probability was almost 0 due to the low radar cross-section (RCS). The authors then reduced the amplitude threshold and permitted detections with lower Dopplers. By this means, they improved the drone detection (true positives) significantly. However, much more false positives were recorded in this case because the radar sensitivity for other targets such as birds, surface targets and clutter was increased. As a solution, the authors used ML by selecting simple time-domain features including the height, the maximum height, the Doppler (radial velocity), the acceleration, and the jerk (change in acceleration). A binary decision tree model was trained which could improve the drone prediction probability to 88% and reduce the false alarm rate to 0. In later papers, the authors utilized newer versions of radar to classify drones vs. birds tracks, however, without the aid of ML [7], [8].

B. CLASSIFICATION OF DRONES vs. BIRDS

Torvik et al. highlighted the importance of classifying drones vs. birds because both targets show low RCS and causes a confusion in the surveillance against non-cooperative drones [9]. They argued that gliding birds and plastic-rotor UAVs are characterized by insignificant micro Doppler signature (MDS) and poor RCS modulation. Therefore, they proposed using polarimetric features for drone detection as reported in radar ornithology and meteorology [10]. The authors used nine polarimetric parameters (linear depolarization ratio, differential depolarization ration, co-polarized

TABLE 2. Summary of related works on radar methods based on machine learning for drone detection and tracking.

Work	Radar System	Range	Classes	Data	Features	Classifier	Results
[6]	L-band holographic radar	1km-500m. Altitude 500 ft.	2 classes: Drone (hexacopter), Non-Drone	5-min flight	Height, max. height, acceleration, jerk	Decision tree	Detection probability: 88%
[9]	S-band BirdRad	0.3-0.4 km	4 classes: two birds and two drones (3-D Solo and DJI Phantom II)	8000 trail samples	9 polarimetric features	nearest-neighbor classifier	Classification accuracy: 100% accuracy
[11]	Ka-band CW radar	2 m in lab. Outdoor experiments without range specification	2 classes: UAVs vs. simulated bird data	30 10-second trials per drone, simulated bird MDS	Mean spectrogram, SVD, CVD	SVM	Classification accuracy: 96% to 100%.
[12]	S-band pulsed radar	-	2 classes: UAV tracks vs. bird track	Bird tracks real. UAV tracks by simulation	20 features extracted from track	ANN with 30 hidden layers	Classification accuracy: up to 100%
[14]	X-band CW radar	less than 30 m	11 classes: 11 drones	30 seconds recording for each drone	Eigenvector and Eigenvalue of MDS	Naive Bayes, linear and non-linear SVM	Classification accuracy: approx. 95%.
[15], [16]	S-band CW	3 m	4 classes: 3 drones and no-drone class	280 images	Spectral correlation function (SCF) of MDS	Deep Belief Network (DBN)	Classification accuracy: above 90% when $SNR >= 0$
[17]	K-band and X-band CW radar	1.2 m	3 classes: Quadcopter, Helicopter, Hexacopter	720 samples each radar/drone	PCA based features	SVM	Classification accuracy: up to 94.7%
[18]	Ku-band FMCW radar	-	2 classes: Inspire 1 and F820	50000/10000 images indoor/outdoor	Contatendated MDS and CVD	CNN	classification accuracy:94.7%
[19]	Pulsed	-	2 classes: Phantom 2 and S1000+	Own database	Virtual scattering points' images	MLP,RNN, FCN	Classification accuracy: from 70% to 100%
[20]	S-band pulsed radar (NetRaAD)	60 m	3 classes: no payload, 200 g payload, 500 g payload	45 samples per class	Centroid and bandwidth of MDS	Naive Bayes and Discriminant analysis	Classification accuracy: 90-100%
[22]	S-band pulsed radar (NetRaAD)	60 m	5 classes: no payload, 200g, 300g, 400g, 500g	45 samples per class	SVD and centroid of MDS	Naive Bayes, Discriminant analysis and Random forest	Classification accuracy: 95-96%.
[24]	CW K-band radar	-	Quadcopter, Helicopter, Hexacopter	140 segments with 0.375s for each segment	cadence frequency spectrum (CFS) features	k-means classifier	Classification accuracy up to 96.64%, 90.49% and 97.8% for single , two and three drones respectively
[23]	-	-	4 classes: single and multi-propeller drones with 2 or 3 blades each	Synthetic database	MDS	MLP, ANN	Aver. classification accuracy: 99%
[11]	Ka-band CW radar	2 m in lab. Outdoor experiments without range specification	2 classes: small-sized drones vs. medium-sized drones	30 10-second trials per drone	Mean spectrogram, SVD, CVD	SVM	Classification accuracy: 96% to 100%.

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correlation coefficient, cross-polarized correlation coefficient, entropy, anisotropy, polarimetric eigenvector, and orientation angle) to train a nearest-neighbor classifier. 8000 real data points from two drones and two birds, which exhibit similar RCS characteristics, were collected using a dedicated S-band radar system called BirdRAD at 3.25 GHz. The classifier showed very high classification accuracy close to 100%.

Fuhrmann et al. extracted three features from the MDS to classify drones against birds [11]. These features include the mean spectrogram, the first left singular vector of singular value decomposition (SVD), and the mean cadence velocity diagram (CVD). The authors obtained data for six drones by operating these drones in a stationary lab setup (drones are fixed at a distance of 2 m from the radar) as well as by flying them different trajectories outdoors, however, without details about the flight range. In contrast, birds' flight data were generated by simulation using the same Continuous-Wave (CW) radar configuration which was deployed to collect drone data. A SVM classifier was trained and the generated model showed a classification accuracy of 100%.

Mohajerin et al. used statistical features of radar tracks to classify UAVs vs. birds and manned aircraft [12]. The non-UAV tracks were generated from real data collected using an air traffic control radar. UAV tracks, however, were generated by simulation. 16 time-domain features were derived from target movement data such as the mean and variance of speed, acceleration, and jerk in addition to features related to the form of the trajectory. Four more features associated to the radar cross section of the target derived from the amplitude of the plot were also employed. An artificial neural network with 30 hidden layers was used where 70%, 15%, and 15% of the data were divided for training, validation, and testing, respectively. UAV tracks could be classified with an accuracy of 100% even with single features. However, it should be noted that the simulation-based generation of data in this paper raises some questions. For example, the drone tracks were generated for long ranges (up to 20 km) and the drone RCS was assumed to be between 1 and 2 m^2. The second assumption is very far from reported results by researchers who investigated the RCS characteristics of different drones. In their review, Patel et al. found out that typical RCS values varies between -30 and -14.1 dBsm [13]. Also the first assumption of a 20-km range is impractical since all other related work could hardly detect a drone beyond a 1-km range.

C. CLASSIFICATION OF DRONES vs. DRONES

Molchanov et al. extracted features based on the Eigenvectors and Eigenvalues of the MDS [14]. They trained a linear and a non-linear SVM as well as a Naive Bayes classifier. Data were collected using a CW radar by flying eleven objects (two fixed-wing, three helicopters, one quad-rotor, an artificial bird, and four stationary rotors) for 30 seconds each. Based on 10-fold cross validation, drones could be classified with an average accuracy of 95%. In a second test, the authors excluded some models from the training and found out that the classifier could still classify them into fixed-wing, stationary rotor, or helicopter with an accuracy ranging from 87% to 100%.

Mendis et al. trained a deep belief network (DBN) to classify drones after extracting the spectral correlation function (SCF) from the MDS [15], [16]. The SCF is the Fourier transform of the autocorrelation function and helps in comparing observations of the distribution of velocities. Three micro-drones (an artificial bird, a helicopter, and a quad-copter) were placed at fixed position three meters far from a CW radar in a lab environment. The authors also generated data without any drone in place as a reference class. Thus, the DBN worked on data from four classes, in total where 70 SCF images were generated for each class. Different levels of Gaussian noise were added to 50 of these images as a data augmentation mechanism. The authors reported that the drones could be classified with accuracies above 90% when the signal-to-noise ratio is equal to or larger than zero.

Zhang et. al. proposed a dual-band CW radar operating in the K-band and X-band to classify three drones: a helicopter, a hexa-copter, and a quad-copter [17]. The drones were fixed in a lab at a distance of 1.3 m from both radar sensors which were placed at a distance of 1 m from each other. First, time-frequency spectrograms were extracted using short-time Fourier Transform (STFT) from the radar data (MDS). Then features were obtained by applying PCA on the spectrograms. Three tests were performed using a SVM classifier: The first two tests worked on features from the individual radars only. In the third test, the data from both radars were fused. 720 samples from each radar sensor and for each drone were collected. 3% of the data were used for training and the rest for validation, whereas the training/testing process was repeated 50 times with a random selection of data. The authors highlighted the superiority of the dual-band solution over single radar solution, although the K-band radar alone is not clearly worse than the dual-radar solution. On average its classification accuracy is only by 1.2% lower than the dual-band solution. In a subsequent work, the authors investigated the detection of two and three drones at the same time as will be described in Section II-E.

Kim et al. investigated the pre-trained convolutional neural network (CNN) (GoogleNet) to classify two drones (Inspire 1 and F820) [18]. While hovering above a Ku-band FMCW radar at two heights (50 m and 100 m), the MDS was recorded and its CVD was determined. The MDS and CVD images were concatenated into one image, which was referred to as merged Doppler image (MDI). 10000 images from outdoor measurements were generated and applied to the CNN classifier using 4-fold cross validation. The results show that the drones could be classified with an accuracy of 100%. Surprisingly, indoor experiments in an anechoic chamber demonstrated lower classification performance.

Brooks et al. modeled a drone by a discrete set of scattering points distributed along its structure [19]. This model is two-dimensional and assumes that the drone is in the same plane with respect to the radar. When the scattering points move, they yield a set of series of 2-D coordinates. The latter are fed to wave equations which return a temporal series of complex points. Then the ground clutter is added by simulation using Billingsley's model. These models were used to generate data for three types of drones (Vario helicopter, DJI's Phantom2 and S1000+). Three classifiers were tested: Fully-convolutional networks (FCNs), Recurrent neural networks (RNNs), and multilayer perceptron (MLP). While the MLP classifier could classify the drones with an accuracy around 70% to 85% depending on the SNR, the RNN and FNC classifier gave higher accuracy approaching 100% when SNR = 30dB. Note that this work does not consider MDS and assumes a pulsed radar. The models are used to generate data from simulation without any range information. It would be interesting to know how this approach would work with real radar data.

D. CLASSIFICATION OF DRONE CHARACTERISTICS

Fioranelli et al. applied ML to identify whether a drone has zero, 200, or 500-gram payload (three classes) [20]. The authors argued that the knowledge about the drone payload is crucial because it can indicate suspicious or hostile activities by malicious users. They utilized the same multi-static radar system NetRAD described in [21] to extract two features which are the centroid and the bandwidth of the MDS in 2-second windows. The three receivers recorded data of a drone hovering at 60 m distance from transceiver for 30 seconds. Thus, 15 samples per receiver for each payload class were collected. Naive Bayes as well as discriminant analysis were applied with cross validation for training and testing. Results were shown for three decision strategies: (i)-Model generated from data of the mono-static receiver (the receiver co-located with the transmitter), (ii)-Model generated by merging data from the three receivers (iii)-Three models, one per receiver and the decision was based on a majority voting scheme. The majority voting gave the best accuracy with a value between 90% and 100%. In terms of the tested classifier, discriminant analysis outperformed the Naive Bayes in terms of accuracy. The authors observed that with increasing payload, the MDS appears "more uniform and straight" and reaches higher positive and negative values which can clarify the good classification results. This is explained by the fact that higher payload requires more blade speed to maintain the drone hovering at the same altitude. In a subsequent work by the same group, the authors extracted the SVD and centroid of the MDS and added random forest to the set of experimented classifiers [22]. In addition, the authors tested two flight cases: (i) hovering and (ii) moving where the attained classification accuracy show slight differences (96% vs. 95%). While the SVD feature was more efficient in classifying the payload in the case of movement, the centroid was more suitable for payload classification when the drone was hovering.

In their paper which we described in Section II-B, Fuhrmann et al. performed additional classification tests to characterize the drones [11]. They divided five of the used drones into a small-sized classes (three drones) and medium-sized classes (two drones). They used the same data, features, and classifier, which they deployed to classify the drones against birds as described in Section II-B. The SVM classifier could identify small and medium-sized drone with an accuracy of 96%. In addition to these classification tests, the authors performed a Cepstrogram analysis in the quefrency domain to characterize the drones according to their number of rotors, the rotation rate, and the rotor blade length. For example, for a specific drone, they could estimate a blade length of 18.5 cm whereas the actual length is 19 cm.

Regev et. al. relaied on theoretical time-domain models for MDS to generate synthetic data for 1 and 4 propeller drones with two or three blades each. The data were used to train a MLP ANN-based classifier followed by regression to estimate the blade length and rotation rate [23]. The environment noise was simulated by adding different levels of SNR. The classification results were very accurate (99% for SNR = 5 dB) and the parameter estimation showed low errors (4% in estimating the rotation frequency and 6% in estimating the blade length). It would be desirable to learn how this method would be extended to address practical drone data.

E. MULTI-DRONE DETECTION

Zhang et al. studied the possibility of detecting multiple drones that are present simultaneously using a K-band CW radar [24]. They converted the time-frequency spectrogram into a CVD and extracted from the latter the cadence frequency spectrum (CFS), which was used as features for training a K-means classifier. In their lab tests, they employed a helicopter, a hexa-copter and a quad-copter to collect data for single UAVs, two UAVs, and all UAVs. They found out that average accuracy results for single drone classification, two drone classification and three drone classification were 96.64%, 90.49% and 97.8%, respectively.

F. DISCUSSION

Despite the wide variety of used radar front ends, extracted features, and classifiers, all reviewed papers report positive classification results which surely gives hope in this technology. On the other hand, it is unclear whether any of the reported solutions can be generalized to cover more drone types, wider ranges, different radar sensors, and different signal processing schemes. Haykin commented "The radar has to learn from experience on how to deal with different targets, large and small, and at widely varying ranges, all in an effective and robust manner" [25]. Most of the research performed in the reviewed papers (and many other papers without ML) can be described as experimental work without sufficient exploration of design alternatives based on an in-depth requirement analysis.

An interesting observation is that the papers which address the ability of ML to classify drones vs. drones or drones vs. birds as well as the contributions on drone characterization (size, payload, etc.) seem to presume detection. This is evident form the experiments which are frequently conducted in setups, which bias the detection schemes. For example, with just a few exceptions, most experimental flights were performed at low ranges under 60 meters and sometimes the drone was even fixed at a distance of 1.5, 2, or 3 meters from the radar in a lab setup. It should be expected that targets at larger distances are harder to detect not to mention classify. With their high-end radar, Jahangir showed that detecting a drone at distances between 500 and 1000 meters is impossible [6]. Their contribution was a clear example of how machine learning can help reduce noise on the data level and help in the detection mechanism. It would be very interesting to see if Jahangir's solution can be extended to a multi-class classification at such distances. On the other hand, it is significant to experiment how the classification models proposed by other groups, would behave at larger distances. Model-based and simulation-based data generation for the sake of classification is another form of presuming detection. Mohajerin commented on their simulation-based approach ''to further validate this claim it is required to improve the fidelity of our simulation and finally perform experimental evaluations'' [12].

Focusing on the classification task and separating it from the detection assignment may sound attractive and justified in order to achieve progress in feature engineering and the development of classification models. However, without reference datasets, the validity of such models is difficult to show. The provision of accessible datasets is a high-priority task for the radar drone detection, as it is for cognitive communication and radar in general [26]. Researchers interested in the preparation of such datasets should spend deep thoughts on finding the most appropriate signal/s that should be made ready for the ML process. As an example, the MDS has been accepted and utilized by most authors and could be a starting point.

Furthermore, many drones are capable and usually fly at high speeds. If they developed research and techniques is limited to only low distances classification, then this would only make sense if the classification technology is fast enough to allow a decision on time. Not all classifiers are equally efficient in real-time. While a linear SVM model, for example, requires a few arithmetic operations to classify a data point, a random forest classifier often requires the traversing of large number of trees, which can take considerable time. The real-time aspects of classifiers will be more important when multiple drones are expected in the sky at the same time.

Moreover, many papers presented the results of one classifier and some tested two or three classifiers. With just one or two exceptions, all classifiers worked well. This is not the case in other fields such as natural language processing and computer vision. In these research areas, researchers sometimes report significant differences in the performance of classifiers on the same dataset [27]. Knowing this, it would be interesting to know why the research on radar drone classification worked with the ''first'' classifier at hand. This is especially compulsive to know because none of the reviewed papers has justified the selection of the employed classifiers. Testing multiple classifiers and features can be very beneficial for the community to pinpoint the limitations and capabilities of each algorithm.

III. ML-BASED DRONE CLASSIFICATION BY VISUAL DATA

Despite its traditional success in target identification and tracking, the radar remains a highly professional technology which requires a trained staff that is capable of interpreting the visual outcomes of the radar system at least for decision making. This complexity of the radar technology and the rapid progress in the computer vision field have invited some researchers to consider drone detection and classification using visual data (images or videos). Contributions in this area can be divided into two categories depending on how authors have dealt with feature extraction. The first category includes solutions which rely on learned features, thus, omitting the extensive step of feature engineering. The other category depends on traditional machine learning schemes which are expected to feed the system with low-level hand-crafted features such as edges, blobs, and color information. Table 3 summarizes related work on ML-based visual drone detection.

A. VISUAL DETECTION WITH LEARNED FEATURES

Rozantsev *et al.* in [28] proposed two methods for the detection of flying drones (UAVs and Aircrafts) from a single camera. The two approaches are based on 3-dimensional Histograms of Gradients (HoG3D) and a CNN model. The proposed system starts by dividing the video frames into overlapping temporal slices with 50% overlapping. Then, a multi-scale sliding window is deployed to generate st-cubes. After that, to avoid any bias to global motion, the authors proposed a motion compensation algorithm based on regression method. To this end, two propositions are made: 1) train two different boosted tree regressors to predict the required translation for an input patch based on HoG features. 2) train two separate CNNs for the regression task based on the learned features. After the training, the regressors are used to compensate the motion and generate the st-cubes which are then fed as inputs for classification. To evaluate the performance of the proposed system, the authors built their own database which consists of two parts a UAV dataset and an aircraft dataset. This database is publicly available. The average precision of the proposed detection method is 0.849 and 0.864 for the UAV and aircraft datasets, respectively. As a final stage, a regressor is trained to accommodate for the different image scales, i.e. it is trained to fit the detected object precisely.

Yoshihashi *et al.* in [29] proposed a deep learning approach namely Recurrent Correlational Networks (RCN) for detecting and tracking small UAVs. The proposed system consists of four networks each with a specific task. The first one is a convolutional layer that represents target and non-target appearances from a single frame. Then the ConvLSTM is utilized to learn motion representations from multiple frames. After that, cross-correlation layers are employed to generate correlation maps between the template and each subsequent

TABLE 3. Summary of related work on visual methods for drone detection and tracking.

Work	Drone	Max. Range	Acquisition Method	Pre-processing	Dataset	Features	Detection Method	Results
[28]	UAVs and Aircraft	NS	NS	Multi-scale sliding window to generate st-cubes	UAV database and Aircraft database	HoG3D, Learned features	Boosted trees, CNN	Average precision is 0.849, 0.864 for the UAV and Aircraft databases respectively.
[29]	Small UAVs	NS	NS	NS	UAV database and video-based bird database	lLearned features	Recurrent Correlational Networks (RCN)	ROC curves demonstrate the superiority of the system.
[30]	NS	NS	NS	NS	Artificial dataset	Learned features	Fine tuning CNN (YOLOv2)	Precision and recall values of approximately 0.9.
[31]	NS	NS	NS	NS	Drone Vs Bird Database	Learned features	Fine tuning CNN (VGG and ZF)	Mean average precision 0.66
[32]	NS	NS	NS	NS	Synthetic database for drone detection	Learned features	Fine tuning Faster R-CNN with ResNet 101	Mean average precision 80.69%
[33]	NS	NS	NS	Camera mounted on a drone	10013 images collected from Google	Haar and learned features	Haar cascaded classifier, CNN	Detection and identification accuracies are 89% and 91.6% respectively
[34]	NS	NS	Smart phone	NS	NS	Geographical distributed data points	Intelligent probabilistic model.	Results show good performance but needs more investigation and improvements
[35]	NS	NS	NS	64×64 resizing and gray-level conversion	1340 images for drones and birds	Generic Fourier Descriptor (GFD)	Neural Network	classification accuracy is 85.3%

frame with the aim to localize the target in the frame. Finally, fully connected layers are used to generate the confidence scores of each object. It should be mentioned that the authors did not train the whole system from scratch. Rather, they followed a fine tuning approach using AlexNet and VGG16. The evaluation of the system was done using two datasets for UAV and birds. The results reported in terms of ROC curves demonstrate that the system outperforms the previous solutions.

Aker etal. proposed an extension of an existing CNN model namely, YOLO, which is a single shot object detector [30]. The new version, YOLOv2, uses a fine tuning technique to train a regerssor for the UAV detection. They have created an artificial dataset to evaluate their system where they attained approximately equal precision and recall values of 0.9.

Saqib *et al.* [31] investigated different pre-trained CNN models including Zeiler and Fergus (ZF) and VGG16 coupled with the Faster R-CNN model for the detection of drones from video data. They used the VGG16 and the ZF model as a transfer learning to compensate for the lack of sufficient dataset and to ensure the convergence during training for the model. The training was done with Nvidia Quadro P6000 GPU where the learning rate was fixed to 0.0001 with a batch size of 64. They used a Bird-Vs-Drone dataset which consists of 5 MPEG4-coded videos recorded in different sessions with a total of 2727 frames and a resolution of 1920×1080 pixels. The results show that VGG16 coupled with the Faster R-CNN demonstrates the best performance with an average precision of 0.66.

Peng *et al.* in [32] addressed the issue of limited visual data for UAVs by creating their own artificial images. They used Physically Based Rendering Toolkit (PBRT) to generate photorealistic UAV images. The rendered images consist of different positions, orientations, camera specifications, background, and post processing methods. After creating the images, the Faster R-CNN network was fine-tuned using the weights from ResNet-101 model for UAV detection. The size of the dataset created is 60480 UAV images where the average precision achieved was 80.69%.

Lee et al. proposed detecting drones from a camera mounted on a different drone [33]. The system relies on Haar feature cascade classifier to detect the drone in the images and a simple developed CNN network for identifying the drone models. The CNN model consists of two convolution layers and two fully connected layers with 30% dropout used in the latter. Adam optimizer was employed to train the network for the identification phase. The dataset was collected manually from Google images, where the total number of drone image is 7000. This includes distorted drone images and 3019 non-drone images. The detection accuracy attained is around 89% while the identification accuracy is 91.6%.

B. VISUAL DETECTION WITH HANDCRAFTED FEATURES

Boddhu *et al.* in [34] proposed employing an intelligent smart-phone application to obtain drone attributes such as speed and height. This is done by integrating a composable sensor cloud and an intelligent probabilistic model. The proposed model utilizes multiple geographical distributed data points for the prediction and estimation of flight path. The results demonstrate the capability of such system to perform the specified tasks; however, more improvements are required.

Unlu *et al.* developed vision-based features namely Generic Fourier Descriptor (GFD) which are robust against translation and rotation changes [35]. These features are used to detect drones from birds by training a neural network model. They perform the training and testing on their own collected dataset using 5-folds cross validation. The dataset consisted of 1340 images (410 for drone and 930 for bird). The attained classification accuracy is 85.3% with the original dataset and 93.10% with a subset of the dataset consisting of only 162 selected images.

C. DISCUSSION

Drone detection and classification based on visual data is still in its infancy. Most of the work was done using learned features by utilizing different deep learning models and approaches. However, it is known that deep learning methods are data driven and require huge labeled datasets to generate robust models. The lack of publicly available datasets is a hard constraint on the research in this area. To mitigate this situation, some authors made use of transfer learning rather than starting from scratch. Other research work such as [32] employed dedicated software to generate synthetic images to increase the number of samples in the dataset. Other techniques for enlarging the dataset that could be used in the future include data augmentation and the utilization of generative models such as generative adversarial network (GAN) for creating artificial data which are similar to the original real data. Most of the research in visual drone detection fails to specify the type of the acquisition device, the drone type, the detection range, and the dataset used in their research. These details are key to validate the work and make it comparable with related literature. Apart from these machine learning aspects, visual detection suffers from its reliance on the presence of a line of sight (LOS) between the drone and the camera system which might mitigate the effectiveness of this modality.

IV. ML-BASED DRONE CLASSIFICATION BY ACOUSTIC DATA

A flying drone produces a humming sound that can be captured by acoustic sensors and analyzed using different methods to identify drone-specific audio fingerprint. An ideal outcome would be to determine the drone type or even the individual drone by its audio fingerprint. In general, acoustic drone detection relies either on correlation/autocorrelation methods or on machine learning classification, see Fig. 2. In this paper we focus on the latter.

Nijim and Mantrawadi [36] presented a feasibility study for drone detection from its sound. They relied on Hidden Markov Model for the detection of DJI Phantom 3 and FPV 250 drones.

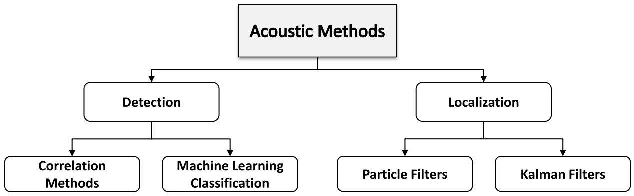

FIGURE 2. **Classification of solutions on acoustic drone detection and tracking.**

Jeon *et al.* proposed using Gaussian Mixture Model (GMM), CNN, and RNN classification to detect the existence of a drone in the range of 150 meters [37]. The authors addressed the lack of acoustic data of flying drone and proposed building datasets by augmenting different environmental sounds with drone sounds. An interesting aspect of their work is using different drones for training and testing the classifiers. They found out that the RNN classifier performed the best (80%), followed by GMM classifier (68%) followed by CNN classifier (58%). The performance of all classifiers, however, drops significantly with unseen data.

Bernardini *et al.* used multi class SVM classifier to identify the drone sound compared to other signals such as crowd and nature daytime [38]. The work involved collecting web audio data using an audio file scraper with a focus on files with sampling rates higher than 48 kHz. The dataset included five 70-min sounds from flying drones, nature daytime, street with traffic, train passing, and crowd. Then the collected data were segmented into 5-second segments for midterm analysis and 20-msec sub-frames for short-term analysis; all with overlapping segments of 10ms. The authors extracted short-time energy, temporal centroid, Zero Crossing Rate (ZCR), spectral centroid, spectral roll-off, Mel Frequency Cepstral Coefficients (MFCCs) as features from the pre-processed signals to train a SVM classifier. The results for detecting the drone sound against the other classes in terms of accuracy is 96.4%.

Kim *et al.* [39] proposed using spectrum images from the sound signals coupled with correlations and k-nearest neighbor (KNN) classifier methods to detect DJI Phantom 1 and 2. Different sound signals were recorded from the drones indoor (without propellers) and outdoor as well as from an outdoor environment without drones in addition to environmental sound from a YouTube video. All recorded sounds were segmented into 1 second frames. 83% accuracy was achieved with image correlation and 61% with the KNN classifier.

Yue *et al.* developed a distributed system to detect the presence and approximate the location of drones utilizing acoustic wireless sensor network (WSN) with ML [40]. By performing several experiments, the authors found that the power spectrum density (PSD) of the drone sound is different from other natural sounds. The PSD is obtained using Fast Fourier Transform (FFT) after prepossessing the drone sound with a low pass filter (LPF) with a cutoff frequency at 15 kHz. The experimentation showed that filtering at this cutoff frequency could eliminate unwanted noise associated with the acoustic signal. After applying PCA as a dimensionality reduction technique, a SVM classifier was trained to identify the drone sound from other sounds (rain, natural background). The dataset was collected from different categories with 20000 samples each. Then 2000 tuples were selected at random and divided into 50, 30 and 20 percent which were used for training, testing and creating overlapping signals for additional testing. Additional Gaussian noise was added for the testing scenario with a signal to interference ratio (SIR) higher than of 10dB. The result demonstrate that the drones were detected successfully with this level of introduced SIR or higher.

Seo *et al.* proposed to use the normalized STFT to create 2D images from drones' acoustic signals [41]. The sound signal was first divided to 20-ms segments with 50% overlapping. Then the normalized STFT was extracted and used as an input for a designed CNN network. The dataset consisted of experimental measurements taken outdoor with hovering DJI Phantom 3 and Phantom 4. It contained 68931 sound frames from the drone and 41958 non-drone frames. The testing was done on this dataset after adding Additive white Gaussian noise (AWGN). The best result was found while training the CNN network with 100-epoch and low SNR in which the detection rate (DR) is 98.97% and the false alarm rate (FAR) is 1.28.

Matson *et al.* proposed to extract the MFCCs and the STFT features from an optimized multiple acoustic nodes system [42]. The features were then employed to train two types of supervised classifiers namely SVM and CNN. For the later, the audio signal was represented in 2D images to be fed to the CNN model. This model consisted of two convolution layers and two FC layers along with pooling and dropout layers. The dataset was collected for two different cases. In the first case, the drone was flying from 0 to 10 m above the acoustic system (which consisted of 6 nodes) at a maximum range of 20m. In the other case, the data was collected without the presence of the drone where the audio recorded was the environmental noise only. One type of drone was tested namely the Parrot AR Drone 2.0. Several experiments were conducted and the results demonstrate that the STFT features coupled with SVM provided the best performance which was reported in terms of color maps.

A. DISCUSSION

From Table 4 and the descriptions of the research works we can see that acoustic drone detection using machine learning is still an emerging area of research. Most related work dealt with drone detection and only a few papers used microphone arrays for localization are available. Like with radar and visual detection, a comparative evaluation of different contributions is very difficult, because the authors used different drones, different ranges, different features, different classification/correlation methods, and different performance metrics. This research is especially hindered by the lack of benchmark data with different types of drones flying at different distances and speeds under different environmental noise conditions. Proposed acoustic detectors have at most 150m detection range. Apart from optimizing the detector with two distances proposed by Hauzenberger and Ohlsson [43], an in-depth investigation of the impact of range on the detection performance is missing in all reviewed papers.

V. ML-BASED DRONE CLASSIFICATION BY RADIO FREQUENCY

In general, UAVs contain an on board transmitter that perform data exchange to control and operate the UAV using an RF signal. Usually, this is in the 2.4 GHz industrial, scientific, and medical radio band (ISM band). With this prior knowledge, the drones can be detected and localized from a wide distance. On top of this advantage of using the RF signal as a detection mechanism for drones, it is also possible to locate the controller used to send the signal which allows us to locate the source of the signal.

Shi *et al.* proposed to use Hash Fingerprint features based on the distance-based support vector data description (SVDD) for the detection of slow, small unmanned aerial vehicles (LSSUAVs) that operate at the 2.4 GHz frequency band [44]. The system initiates by detecting the start point of the original signal, generating envelop signals and then extracting the envelops from the signals. Following that, hash fingerprint is generated as feature to train a SVDD. The authors have collected their own dataset to evaluate the system. The results demonstrate that the system is capable of detecting and recognizing LSSUAV signals in an indoor environment. However, when an additive white Gaussian noise is added the system performance deteriorates.

Nguyen *et al.* investigated a system that consists of different algorithms to detect drones from its physical attributes [45]. The system takes the drones RF signature based on two key features which are body shifting caused by the spinning propellers and body vibration from the navigation and environmental factors. The former was detected using wavelet analysis while the latter utilized the dominant frequency component that has a maximum PSD through the STFT. The evaluation was done for two different types of drones namely Parrot Bebop and DJI Phantom. Two experiments were performed to characterize the movement of the drone using inertial measurement unit (IMU) and wireless sensing hardware. The maximum tested range was 600 m. The results illustrate the system accuracy of 84.9%, a precision of 81.5% and a recall of 90.3%. However, when the range was reduced to 10 m the system performance increased to reach 96.5% (accuracy), 95.9% (precision) and 97% (recall).

Ezuma *et al.* developed a system that convert the raw RF signals into frames in the wavelet domain, as a preprocessing step, to reduce the size of the data and remove any bias in the signal [46]. A Markov model was employed to describe the presence or absence of a UAV in the frame. A naive Bayes classifier was then used for detecting the UAVs from the frames. To classify the different types of UAVs, the energy transient signal was used since it is more robust

TABLE 4. Summary of related work on acoustic methods for drone detection and tracking.

Work	Drone	Max. Range	Acquisition Method	Pre-processing	Dataset	Features	Detection Method	Results
[36]	DJI Phantom 3 and FPV 250	NS	NS	NS	NS	NS	HMM	Very preliminary results that show the feasibility of detection.
[37]	DJI Phantom 3 and 4, DJI Inspire, 3RD Solo	150 m	Augmenting background sound (recorded in public) with drone sounds (recorded in a quiet outdoor place)	Frequencies below 1.5 kHz are filtered. Window length 40 ms (GMM) and 240 ms (CNN, RNN)	9556-sec augmented sound (training), 151 sec (testing), 1557 sec (unseen data)	MFCCs	Binary classification: GMM, CNN, RNN	Best accuracy with RNN (80%) followed by GMM (68%) followed by CNN (58%). Low performance with unseen data.
[38]	NS	NS	Web data collected from audio file scraper	Divide the sound into segments of 5-second and 20-ms with overlapping of 10ms	Five 70-min sounds from the classes	Short-time energy, temporal centroid, ZCR, spectral centroid, spectral roll-off, MFCCs	Multi-class SVM	Classification accuracy of 96.4%
[39]	DJI Phantom 1 and Phantom 2	NS	Drone sound recording indoor (without propellers) and outdoor. Environmental sound recording outdoor without drone. Environmental sound from a YouTube video	1-second frames	NS	Spectrum image and FFT amplitude spectrum.	Correlation and KNN classifier	83% accuracy in image correlation 61% in KNN classification
[41]	DJI Phantom 3 and Phantom 4	-	Yeti Pro microphone	Sound segmentation to 20ms with 50%	68931 sound frames for drones and 41958 sound frames for non-drones others	Normalized STFT	CNN	DR is 98.97% and FAR is 1.28 with 100-epoch and low SNR environment
[40]	-	-	-	LPF and PCA	2000 tuples sampled for drone and non drone sounds divided 50%, 30% and 20%	PSD	SVM Classifier	Best TPR and FNR when SIR is greater than 10dB.
[42]	Parrot AR Drone 2.0	75m	Multiple acoustic nodes system	-	Drone and environment noise audio signals	MFCCs, STFT	SVM Classifier, CNN model	STFT-SVM show best detection accuracy in terms of color map.

to different noises and easier to modulate. For this phase, the distribution of the energy time frequency was employed to generate a normalized energy trajectory of the signal. After that, the beginning and ending points of the energy transient were identified by finding sudden instantaneous changes in the trajectory. After that, some statistical features were extracted namely skewness, variance, entropy and kurtosis where then the Neighborhood component analysis (NCA) was implemented on the computed features to reduce their number and select the most robust ones. Finally, different classifiers were investigated yet the kNN achieved the best classification performance. The evaluation process was done on a dataset consisting of 100 RF signals coming from 14 different UAV controllers. The training and testing was done on partitioning basis where 80% of the data used for training and 20% for testing. The results demonstrate an average detection accuracy of 96.3%. The authors also reported results for different SNR levels whereas an SNR less than 10dB gave bad performance while an SNR of 12dB or higher attained an accuracy of 100%.

A. DISCUSSION

The RF signal is an important characteristic of drones which can be employed for the purpose of detection and localization. However, RF based solutions fail when the drone is operated in a partially or fully autonomous mode. In such cases, the drone usually flies using preprogrammed GPS way points with limited RF-based communication with the ground station. Additionally, the deployment of machine leaning techniques for this type of data is new and the literature lacks a comprehensive public dataset for RF signals which could be used for validation and comparison. Furthermore, all the existing methods have limited performance for low signal to noise ratios. Finally, most related work relied on

TABLE 5. Summary of related work on RF methods for drone detection and tracking.

Work	Drone	Max. Range	Acquisition Method	Pre-processing	Dataset	Features	Detection Method	Results
[44]	LSSUAVs	NS	NS	Generation of envelop signal	NS	Hash fingerprint	SVDD	Secssful detection in indoor environment in 2.4GHz band without noise
[45]	Parrot Bebop, and DJI Phantom	600m	NS	NS	NS	Body shifting, body vibration	Wavelet analysis and maximum PSD	Accuracy of 96.5%, precision of 95.9% and recall of 97% for 10m distance
[46]	Controller for different UAVs	NS	6-GHz bandwidth Keysight MSOS604A oscilloscope with maximum sampling frequency of 20 Gsa/s, 2 dBi omnidirectional antenna, and 24 dBi Wi-Fi grid antenna	Data reduction and bias removal using wavelet transform	100 RF signals from 14 UAV controllers	Skewness, variance, entropy and kurtosis with NCA	SVM, DA, ANN and KNN classifiers	96.3% detection accuracy with KNN classifier and good SNR value.

indoor experiments which do not resemble real application scenarios in which the RF signal might be deteriorated, jammed, or interfered.

VI. CONCLUSION

In their ''Clarity From Above'' report, PwC predicted that the global market for commercial drones will grow to more than 127 billion dollars with key applications in infrastructure, agriculture, transport, security, media, insurance, telecommunication, and mining [47]. However, drone operation is associated with high risk for people and assets. Authorities are working hard toward regulations for drone operation so that less disruptions are recorded. In some cases, these regulations are also supported by ICT solutions to improve the authorization and notification process such as the Low Altitude Authorization and Notification Capability (LAANC) by the USA Federal Aviation Administration (FAA) [48].

Rules and supportive technologies are good for those who follow them but not for careless or malicious users. Systems which are able to keep overview of what is going on are required in the low-altitude airspace, to run a continuous risk assessment, and to interdict in the case of violation. A major task towards this goal is being able to detect, classify, and identify drones in the sky. The expected growth in the drone market and the associated increase in the number of drones in the sky will challenge this task and question the efficiency of human-centered solutions. Machine learning can play a key role in this respect as was shown in this review. The digital processing of different modalities has made machine learning applicable in every detection system as long as the system operator is ready to pay attention to data.

Issues related to the quantity and quality of data in machine learning are well known. But in the case of drone detection and classification, these issues can be described as urgent due to the high business pressure on the one hand and the high risk of operation on the other. Collaborative efforts to build publicly available datasets are indispensable to help researchers and developers build robust classification models for drones based on all modalities.

The risk associated with drone operation strongly depends on the drone location and how far from critical areas it flies. Therefore, ranging should actually be a very important objective. However, as shown in the review researchers have focused on the detection performance and–in the best case–information was given about the drone distance at which the drone was detected. No study was presented which investigated the classification performance as a function of drone distance not to speak of determining the range using regression models. This can be a very interesting research area in the future.

As discussed in the introduction (see Table 1) no single modality is perfect for drone detection and classification. Therefore, several authors suggested bi-modal and multi-modal systems with promising results [49], [50]. Regardless of the used modalities, all proposed solutions go from the perspective of a statically located detection system. In modern cities, this model is very limited because the detection capability can be deteriorated by many obstacles blocking the view, the RF and the radar signal as well as by high noise levels making acoustic detection more difficult. Distributed and collaborative detection systems using wide-area solutions or city-wide surveillance sensors can present a very useful way for the problem of drone detection and classification.

ACKNOWLEDGMENT

The authors would like to thank Prof. Ernesto Damiani for his comments on the paper.

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