Unmanned Aerial Vehicles Sensor-Based Detection Systems Using Machine Learning Algorithms

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***Abstract*— Detecting Unmanned Aerial Vehicles (UAVs), also known as drones, is becoming more difficult as technologies keep advancing. The low price, smaller size, and high speed of UAVs make them hard to detect. The goal of this study is to critically review and evaluate the UAVs sensor-based detection systems using Machine Learning (ML) algorithms. The study reviews several sensor-based detection systems (acoustic, thermal infra-red, radio frequency, and radar), and makes recommendations for future enhancements using machine learning-based techniques. One of the findings of this study is the small amount of data used by researchers, due to the lack of publicly available datasets, which added limitations to the research and may have produced inaccurate results. Another important finding is the closed environments (labs) that most researchers have conducted their research in, which are far from real case scenarios. Finally, this research makes recommendations on how to improve the process and obtain more accurate results. Classification and identification of UAVs are beyond the scope of this paper.**

***Index Terms*—unmanned aerial vehicle, sensor-based detection, machine learning**

I. INTRODUCTION

The use of Unmanned Aerial Vehicles (UAVs) has witnessed an unprecedented increase in recent years. The reason for this huge increase is the wide range of applications that UAVs can cover, including military operations, smart farming, borders and airports surveillance, and more. And the fact that commercial UAVs can be obtained (purchased) easily, or even made, by individuals who are not controlled by aviation authorities, makes life harder and could put lives on risks. According to Caron [1], by 2024 the FAA could have as many as 800,000 registered commercial drones. That's twice the number of commercial drones the FAA registered in 2020.

The no (or weak) regulations in place could open doors wide for probable espionage in sensitive entities, including atomic and nuclear stations. The need has arisen, more than ever, for proper and robust detection systems that enhance the chance of eliminating or reducing any future risks.

Concerns are rising as recent incidents demonstrated the difficulty of detecting small size, light weight, low speed, and low flying UAVs. On 17 April 2016, an incident took place, and reported by Wild et. al [2], when a UAV struck an airplane that belongs to British Airways, at Heathrow Airport. A similar incident occurred in December 2018 when drone sightings disrupted more than 1,000 flights in and out of Gatwick Airport in London, England. The incident, according to the BBC News [3], cost the authorities close to half a million pounds. According to the Daily Mail [4], the latest incident took place in February 2022 when a man was arrested for flying a small UAV over the royal family palace in Sweden. These are some of the recently reported incidents that show clearly how this technology could be used to invade privacy, security, and safety of organizations and individuals.

This paper acknowledges the danger of malicious and undetected UAVs on our daily lives. The aim of this paper is to review the most recent research in UAVs detection using sensor-based Machine Learning (ML) algorithms. The scope of this paper is limited to the detection systems related to acoustic, thermal infra-red, radio frequency, and radar. The goal is to highlight the advantages and disadvantages of each detection technology and make a recommendation on how to enhance these technologies using ML algorithms.

II. LITERATURE REVIEW

UAVs technology is a non-stop growing technology, that produces new models, sizes, and capabilities. The more advanced these models are, the harder to detect. Recent years have witnessed a tremendous effort, by researchers, in an attempt to minimize the threat caused by these malicious and undetected UAVs.

The aim of this section is to highlight the recent UAVs sensor-based detection technologies using ML.

A UAV is originally a military aircraft that is guided autonomously, and in some cases by a remote control. It is capable of carrying sensors, target designators, offensive ordnance, or electronic transmitters designed to interfere with or destroy enemy targets. UAVs come in different shapes, sizes, and capabilities, and are still classified as either commercial or military. They are also classified as

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rotary or fixed wings. Keeping these UAVs under control is far from being easy. Countries like the USA and part of Europe have introduced certain regulations to have UAVs under control. In fact, The FAA Report [5] mentioned that the US government has introduced 'drone regulation' in 2015.

Hayat et. al [6] argued that although UVAs were originally intended for military use, civilian applications are growing by the day, and this is due to the low cost, high mobility, and remote control. Counter UAVs (C-UAVs) technology serves militaries and civilians in war and peace times. It can be essential in protecting air and ground military bases, as well as civilian airports, stadiums, and power plants from attacks. C-UAVs may include border protection (Abushahma et. al) [7], surveillance (Yang et. Al) [8], image processing (Horstrand et. al) [9], and traffic control (Niu et. Al) [10], just to name a few. According to Michel et. al [11], the Director, U.S. Defense Threat Reduction Agency, stated during an interview that the threat of UAVs continues to develop gradually every three to six months, and it will continue to do so due to the adaptive nature of the issue. He added that it is very hard to relay on one technique to deal with a such issue.

While researchers are trying hard to develop a reliable UAV detection system, other groups are also working, in the opposite direction, trying to improve the UAVs ability in detection avoidance. Countering a UAV is harder than it seems. Michel et. al [11] argued that the process involves interaction between many mechanical and electronic systems, in addition to the operators. Several recent researchers suggested generic detection systems (acoustic, video, thermal, RF, and radar), while others try to combine two or more of these systems.

UAVs come in a variety of sizes, and therefore are dealt with differently in terms of detection systems choice. Sturdivant & Chong [12] classified UAVs based on mission range and payload, as shown in Table I.

TABLE I. CLASSIFICATION UAVS STURDIVANT & CHONG [12]

Size Class	Size Mission Range	Payload (kg)
Nano	100 – 500 m	> 0.2
Micro	5 km	0.2 - 0.5
Mini	25 km	0.5 - 10
Small	50 - 100 km	5 – 50
Tactical	> 200 km	25 - 200

One of the challenges researchers face today is the rapid advancement of UAV technology. This technology is moving fast that makes future prediction an almost impossible task. According to Eriksson [13], the UAV's size, weight, range, payload, and speed are the most important parameters to be considered when selecting the right detection system.

The Current Detection Systems

There are several systems that are currently used to identify and detect UAVs: Radio Frequency (RF) sensing (Nguyen et. al) [14], Wi-Fi sniffing (Bisio et. Al) [15], acoustic sensors (Guvenc et. al) [16], video surveillance (Sturdivant & Chong) [12], and radar systems (Birch et. Al) [17]. The following section explains in detail the latest technologies used in the detection of UAVs. Furthermore, the advantages and disadvantages of these technologies are explained in Table II.

TABLE II. COMPARISON OF ADVANTAGES AND DISADVANTAGES OF DIFFERENT DETECTION TECHNOLOGIES. TAHA & SHOUFAN [22]

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 prone to noise as opposite to acoustic detection. Radar doesn't 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	Doesn't 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 daytime. High-cost thermal, laser-based, and wide field-of-view cameras may be required. LOS is necessary.
Radio Frequency	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.

Sensor-Based Technology

Each detection system has its own strengths and weaknesses. Based on Larson et. al [18], a good and reliable detection system would combine multiple strong systems. Sturdivant & Chong [12] arrived at the same conclusion, emphasizing that multi sensor detection systems are more efficient. According to Khaleghi et. al [19], multi-sensor fusion, which is also known as multi-sensor information fusion, is a new technology originally assigned for the military needs, such as surveillance, remote sensing, and guidance and control of autonomous vehicles.

According to Guvenc et. al [20], detecting/tracking UAVs can be enhanced using simultaneous information from a multiple sensors' technique. Samaras et. al [21] emphasized that this technique compensates for the weaknesses of the individual sensors and produces more accurate results. Furthermore, Taha & Shoufan [22] presented a comprehensive summary of several types of sensors used in detecting UAVs. The summary also outlined the limitations and specifications of each type.

Machine Learning-Based Techniques

ML is a subset of Artificial Intelligence (AI), and it is based on learning from relevant data. According to Oxford Dictionary, machine learning is '*a type of artificial intelligence in which computers use huge amounts of data to learn how to do tasks rather than being programmed to do them*'. These huge amounts of data are known as *datasets*.

ML is currently used in many applications, including UAV's detection and recognition, and this is because of its ability to recognize certain patterns without a need to have a human in the loop. Multimodality is an important feature in ML. It can relate data from multiple sources, which humans cannot do. There are several algorithms available that can be used in ML. Some of the most popular algorithms are Decision Tree, Bayes Theorem, Support Vector Machine (SVM), Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN).

In ML, features are extracted from images and fed into a model that is created to predict the nature of the target. With Deep Learning (DL), the feature-extraction step can be skipped, and instead the image can be directly fed into the DL algorithm, which predicts the target. And to choose between ML and DL, the high-performance Graphic Processing Unit (GPU) and the quantity of labels are taken into consideration. If these are available then DL is a good choice, and if either of them is not available, the ML is selected over DL. This is because DL is more complex and needs at least a few thousand images (in the case of infrared thermal camera) to get reliable results. Also, a high-performance GPU is needed so the model spends less time analyzing those images. Having mentioned that, DL has become very popular recently because it is highly accurate and there is no need for someone to understand which features are the best representation of the object.

Taha & Shoufan [22] argued that many researchers tried to identify the UAV type by ML-classification. They added that they were referring to multi-classification with as many classes and labels as the number of identifiable UAV types. Multi-class classification was also used to specify the UAV itself, e.g., by determining the number of its rotors.

If ML is selected, one will have the option to train the model in many different classifiers. One may also know which features to extract, which produces the best results. With ML it's also possible to combine several approaches. Having the options of using different classifiers and features improves the chance of getting best results possible for the given data. Table III provides a quick comparison between ML and DL.

TABLE III. COMPARISON BETWEEN ML AND DL

	ML	**DL**
Training Dataset	Small	Large
Choose your own features	Yes	No
Number of classifiers available	Many	Few
Training Time	Short	Long

Radars

A radar is a device that works on the principle of detecting reflected electromagnetic signals from a target. Radars provide more than the range of the target. In fact, they could provide direction, height, course, and speed. Radars are susceptible to interference from various sources, like weather and surface clutter, which could provide false alarms. Although radars have proved to be effective especially in detecting larger airplanes and missiles, they are not so when UAVs are involved.

According to Oh & Lin [23], deploying radars for the purpose of detecting UAVs is considered an expensive solution, and therefore infeasible. Shi et. al [24] argued that a legal issue could be raised as a result of using high power electromagnetic signals emitted by radars in urban areas. A study on marine radar system by Laučys et. al [25] concluded that detection of micro-UAVs by a radar is possible, provided that it does not exceed a range of 500 meters. The study also concluded that detection of fixed wing UAVs is simpler than that of rotary wings UAVs.

Taha & Shoufan [22] divided the users who apply ML to radar signals into categories: drone detection, classification of drones vs. birds, classification of drones vs. drones, drone characterization classification, and multi-drone detection. Dealing effectively with different targets and at various ranges, according to Haykin [26], is something radars can learn. One observation by Sturdivant & Chong [12] is that research papers that discussed ML's ability to classify targets (birds versus drones and drones versus drones) appear to be assuming detection.

Many researchers used the radar technology in their experiments and claimed to have accurate results. Most of these experiments were conducted in labs at low ranges (tens of meters) and very low altitudes. This does not deflect the reality. In real case scenarios large ranges and higher elevations are harder to detect, not to mention the ability to classify the targets. For example, Jahangir & Baker [27] demonstrated that it is impossible to detect a UAV at a range between 500 and 1000 meters, using high-end radar.

Acoustic Sensors

The simplest, most obvious, and most popular in UAVs' detection is the use of acoustic sensors. These sensors are designed to pick up specific high-pitch signatures from flying UAVs. Eriksson [13] argued that one main disadvantage of this system is the limited range, which does not go beyond a few hundred meters, in an almost noise-free environment. The fact that acoustic (ultrasonic) sensors transmit and receive signals at a speed of sound makes a delay in response inevitable. Mezei et. al [28] explained that several researchers investigated the detection of UAVs using acoustic sensors. Eriksson [13] demonstrated that a 500 meters distance between the acoustic sensor and the target UAV results in 1.5 seconds of delay. This time is enough for a UAV to travel an additional distance of 30 meters before the sound wave is picked up by the sensor, and before any action is taken to stop or destroy the UAV. An additional drawback of the acoustic sensor is its susceptibility to rain and wind. A cluster of acoustic sensors may be used to help detect noise/sound from flying UAVs.

Acoustic sensors can serve the purpose of detecting UAVs in a cheap and straightforward way. Most modern UAVs are designed to minimize the possibility of being detected because of the sound/noise they make. The sound/noise of UAVs depends on a variety of parameters like size, weight, altitude, and type of motors used. A Higher altitude is related to a wider wingspan. It also depends on the application; military applications are not concerned with the noise produced. Uragun & Tansel [29] argued that well designed propellers and rotors (inside the motors) can reduce the sound/noise produced, especially at low altitudes.

Adopting ML classification to detect a UAV, by its acoustic fingerprint, is still a challenging task. Bernardini et. al [30] attempted to compare a UAV sound and compare it to signals coming from surrounding nature, using a multi class SVM classifier. They used a dataset that contains five 70-min sounds from flying UAVs, surrounding nature daytime, cars, busses, trains, and humans. They claimed that accuracy of detecting UAVs between surrounding noises (sounds) was 96.4%. Other researchers Kim et. al [31] and Seo et. al [32] claimed detection rate accuracies of 83% and 98.97%, respectively.

Mezei et. al [28] conducted their research on UAVs' detection using Digital Signal Processing (DSP). A similar study by Bernardini et. al [30] used a combination of DSP and SVM. Other researchers, like Kim et. al [31], developed an approach to target UAVs detection using DSP combined with two machine learning algorithms: the Plotted Image Learning (PIL) and the K-Nearest Neighbor (KNN).

With all this research taking place, challenges still exist. According to Guvenc et. al [20], some of the most important challenges facing the method of detecting the presence of UAVs are the noise that could affect the overall performance of these devices, and the little (or no) availability of the various types of UAVs acoustic data. Al-Emadi et. al [33] emphasized this fact when they acknowledged that the lack of datasets hinders the effort of implementing a practical and effective solution using DL. They introduced an autonomous system that is capable of detecting and identifying UAVs based on their acoustic signatures. This autonomous system is based on deep learning techniques; the CNN, RNN, and CRNN.

Infrared Thermal Cameras

Some detection systems (like radars) are sophisticated and require special trained staff. This made researchers think of other alternatives like visual cameras. Different researchers (who implemented different ML systems, in detecting UAVs), claimed different accuracies. For example, Rozantsev et. al [34], Saqib et. al [35], and Lee et. al [36], claimed accuracies of 0.849, 0.66, and 0.916 respectively. Unlu et. al [37] proposed vision-based features (Generic Fourier Descriptor), which were used to detect UAVs, by training a neural network model. They conducted the training on their created dataset. They were able to distinguish between birds and UAVs, through 410 images of UAVs and 930 images of birds. As a result, they were able to achieve an accuracy of 85.3%. Some researchers have other opinions on the visual UAVs detection. According to Taha & Shoufan [22], most of the studies on visual drone detection fell short of specifying the type of the acquisition device, the drone type, the detection range, and the dataset used.

Detecting flying UAVs in some circumstances (low visibility and during nighttime) can be challenging. Thermal Infra-Red (TIR) cameras can detect a variation in heat as small as tens of milli kelvin. Andrašia et. al [38] conducted an experiment on three different UAVs, using a low-cost thermal infrared, low resolution (80x60 pixels), camera, and tried to demonstrate the UAVs' detection. They concluded that the main source of heat detected was the batteries and not the UAV motors and/or speed controllers (they generate smaller thermal footprint), and this is because batteries are not receiving enough air circulation. Furthermore, they demonstrated that human interpreters are essential for accurate detection.

Using high resolution (320 x 256 pixels) TIR combined with a learning machine technique that automatically detects, and possibly classifies and tracks UAVs, will be a significant improvement. In their research, Wang et. al [39] described the combination of sensors with deep-learning-based detection modules. The infrared videos used have high resolution (1920 x 1080 pixels). They also demonstrated the possibility of using a modified Cycle-GAN (General Adversarial Network) to produce synthetic thermal training data.

Radio Frequency

Radio Frequency (RF) technology is popular in flying and controlling UAVs. RF-based UAVs and their ground controlling units can be detected from long distances. The RF based detection system relies on the assumption that a UAV and its base station are communicating through the RF system. Many studies were conducted on detecting flying UAVs using ML techniques. Al-Emadi & Al-Senaid [40] proposed a UAV detection technique, using CNN. They detected the RF signal during communication between the UAV and the base station, for three different types of UAVs. The proposed technique was tested using a public dataset. The researchers concluded that their proposed technique provided better results than other techniques that used deep learning algorithms. They claimed a detection accuracy of 99.7%.

Other researchers claimed success of other approaches in detecting UAVs using RF technology. Medaiyese et. al [41] implemented the eXtreme Gradient Boosting (XGBoost) algorithm and claimed an accuracy of 99.96% (whether a UAV exists or not), and a 90.73% in determining the type of UAV detected. Al-Sa'd et. al [42] used an RF database to detect and identify malicious UAVs. They implement three Deep Neural Networks (DNN); availability of UAVs, availability of UAVs and their forms, and availability of UAVs, their form, and flight mode. They demonstrated the feasibility of the UAVs detection using the proposed RF database.

In their experiment, Ezuma et. al [43] converted the RF signal in to frames to remove any bias, before using Markov model to indicate the presence or no-presence of any UAV in the RF signal. This was followed by adopting a Naïve Bayes classifier to detect UAVs in the frames. The experiment was conducted on 14 different UAV controllers, which produced a dataset of 100 RF signals. The results demonstrated a detection accuracy of 96.3%.

A similar experiment to detect UAVs, based on physical features using various algorithms, was conducted by Nguyen et. al [44]. One of these features is the UAV's body shifting, which is caused by the spinning of the propellers. This feature is detected using wavelet analysis. The other feature is the body vibration, which caused by navigation in addition to other external factors. This feature makes use of the dominant frequency component. The proposed system considers the UAVs RF signatures based on these physical features. The experiment was conducted at a maximum range of 600 meters and demonstrated an accuracy of 84.9%. The accuracy was increased to 96.5% when the range was reduced to 10 meters.

Most researchers stress the lack of availability of datasets. The lack of publicly available datasets is hindering the research effort towards achieving more accurate results. This was stated clearly in Samaras et. al [21] statement regarding the infrared thermal camera. They stated that '*the creation of a dataset for UAV detection and classification based on thermal images without an increased budget might be out of reach for many universities and research centers'*. Having said that, one can argue that there are certain sites where datasets are available, but not to the public. Unlu et. al [45] mentioned that one of the reasons datasets are not available to the public is due to confidentiality.

III. Discussions

Due to the availability, ease of use, and low cost of UAVs, they become effective tools in creating hazards. UAVs can be used to harm individuals as well as organizations: civilians and militaries alike. The harm that unwanted UAVs can cause depends on their location and how far they are from the intended target. C-UAVs technology continues to advance in a non-stop effort to try to minimize the consequences of the misuse of UAVs. Although governments and authorities are trying hard to implement strict regulations, incidents still happen and could even increase in the future as UAVs technology advances. Several researchers attempted to address the concerns of malicious UAVs, and proposed detection and classification techniques in attempt to prevent or minimize the harm.

Detection of UAVs, based on ML and DL algorithms, using acoustic sensors, IR cameras, RF, radar, and sensor-based technology is relatively new, but it is getting a lot of momentum. The proper application of ML and DL algorithms depends on building public datasets and making them accessible to individual researchers and research centers. This will aid in building robust and reliable detecting system models based on all modalities, as no individual modality is perfectly capable of detecting all UAVs.

Detecting UAVs using RF technology was addressed by many researchers. Besides being an inexpensive technology, RF detection system is capable of detecting intruding UAVs and their controllers. It is also capable of tracking multiple targets at relatively long ranges. Most literature lacks public datasets for RF signals. One of the key findings of these researches is that most of these UAVs detection experiments were conducted in closed environments. These findings do not represent real-life scenarios, and this is because RF signals can be easily jammed. It also can be impacted by severe weather conditions, in addition to being susceptible to interference and noises. One of the drawbacks of using RF-based detector system is the inability of the detector to detect a UAV that is not in communication with its base station (controller).

Detecting UAVs using acoustic sensors is probably the cheapest and most used. One of the drawbacks of this system is the limited range and possible impact of weather conditions. Furthermore, the delay in signal detection due to the use of sound signal could be vital in certain situations where immediate actions are needed to be taken. Advanced UAVs are designed to produce quitter sounds, and this makes their detection even harder. So, for this system to be robust and effective, datasets should be available and updated continuously.

TIR cameras are more sophisticated and can produce more accurate results, if used properly. Most researchers concluded their results and detection accuracies based on experiments with relatively small datasets (tens or hundreds of images). Using ML or DL with such poor datasets produces inaccurate results. One key finding of this review is that relatively large UAVs can be detected easily within certain ranges, using TIR cameras, while small UAVs do not produce enough heat, and therefore they can't be easily detected.

To overcome the problem of ranges, radars can be used despite being expensive and hard to deploy. In certain scenarios where swift actions are needed against malicious UAVs, especially in sensitive entities like nuclear and power stations and airports, radars in combination with other technologies are recommended. Radars can produce accurate results in poor visibility during severe weather conditions and for long ranges. Most radars are designed to detect flying objects at high speed and altitude. Conventional radars are incapable of detecting small UAVs at low speed and altitude.

IV. Conclusions

ML and DL detection algorithms are the most used approaches in UAVs detection. The application of sensor-based technology in UAVs' detection, using ML algorithms, is a fast-growing research topic. It uses data from one or several sensors in the form of images, audio, RF signals, and radar signals. The non-availability of public datasets for such detection systems renders the researchers' ability to provide a robust and reliable detection system using ML and DL algorithms.

Several researchers used DL algorithms rather than ML algorithms, as detection techniques, and claimed to have high accuracies. They also claimed that they did not have access to public datasets. That would put a question mark on the accuracy of the results they produced. Besides, in the DL case, the model will need a long time to train. It can be concluded that the choice between ML and DL depends on the data available and the problem one is trying to solve.

Several researchers conduct their experiments in labs or in small and closed areas. These places are limited in the availability of space and height, which would produce results that are not applicable to real case scenarios, where UAV are flying high and at high speed. Not to forget weather conditions and other parameters that could impact the detection process. A high success rate in the detection of these UAVs inside closed areas (labs) does not guarantee similar results when experiments are conducted in open air scenarios.

None of the UAVs detection methods is effective by itself. A combination of more than one method can produce a more robust, effective, and accurate results. Radar systems are expensive and difficult to deploy but are considered more accurate than other detection systems. They can operate accurately at long ranges. A combination of a radar and an acoustic system would achieve a better result than a single system.

Detection of fixed wings UAVs is relatively simple because they are easy to detect among clutter, while detection of slow UAVs can be harder.

Finally, public datasets need to be available for researchers, at research centers and academic institutions. A collective and collaborative work should be in place to help establish and grow datasets, that should be available for public, for free, to help researchers in pursuing their effort and producing effective, applicable, and robust detection systems based on ML algorithms.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication.

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