UAV Detection and Identification: A Comparative Review of Current Methods and Future Directions

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Abstract

Unmanned aerial vehicles (UAVs), also known as flying robots or drones, were used exclusively for military purposes only in the early 1990s. Now drones are easy to use and inexpensive; therefore, they are easily accessible by individuals as well as organizations. The rapid development of UAVs provides facilities in various sectors, including agriculture, delivery, surveillance, videography, photography, rescue and search operations, and more. Indeed, the expanded use of UAVs contributes to various technical, security, and public safety challenges and has intensified the need for advanced UAV detection and identification systems. This review explores the latest techniques for detecting and identifying drones, focusing on new strategies to tackle the growing concerns around UAVs. We categorize and examine various detection methods, like radar sensing, radio frequency (RF) sensing, sound-based, and vision-based techniques, noting their benefits and drawbacks. Furthermore, this review highlights the importance of other methods, like RF fingerprinting, to improve the precision and efficiency of UAV detection and identification systems, thus increasing security against potential UAV threats.

Keywords: Audio Sensing, RF Fingerprint, Radar Sensing, Visual Sensing, Unmanned Aerial Vehicles (UAVs), UAV Detection, UAV Identification.

1. Introduction

Unmanned Aerial Vehicles (UAVs), commonly referred to as flying robots or drones, have seen a considerable rise in usage across multiple industries owing to their adaptability and ability to operate without an onboard human pilot. These UAVs can either be piloted remotely using ground control systems or flown autonomously through pre-set flight paths. According to the USA FAA (Federal Aviation Administration), commercial and recreational drones are expected to reach between 1.39 million and 1.66 million units. According to the FAA's forecast, the number of non-model drones for aerial photography, agriculture, delivery, and surveying services will be nearly 835,000 [1]. Though the usage of UAVs is great, as we know, in the early days, UAVs were only military-oriented, but now, it has become easier and cheaper for an ordinary person to carry out his daily activities. In the early days, UAVs were commissioned alongside developed countries' military forces for spying purposes, intelligence gathering, heading, and fighting missions. With altering economic models of advanced production techniques and a decline in the costs of manufacturing units, UAVs have been rapidly and progressively gaining popularity among the general public. Today, drones are utilized by businesses, researchers, hobbyists, and people around the world, not just by military and

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government agencies. The reduced cost and great accessibility of these unmanned aerial vehicles have greatly increased their usage in different sectors and for many other purposes as well. The increase in the demand for UAVs all over the globe has brought about new industry-wide advancements, such as use in air photography, videography, surveillance, GPS mapping, search and rescue, transportation, agriculture, and many more [2]. According to a recent report from India, the global commercial drone market is projected to expand from $10.98 billion in 2023 to $54.81 billion by 2030 [3].

The present review paper highlights the gaps in the security achieved by existing technologies and algorithms for detecting and identifying drones in use currently and how safety-related concerns can be addressed. The goal is to provide a detailed summary of the current technologies and those under development. The analysis includes a combination of methods that enable detection, such as radar, RF analysis, and the use of acoustic sensors and cameras. In addition to that, the paper emphasizes other detection methods, especially RF fingerprinting, which can be useful in increasing the success rates of UAV detection and identification systems. This review paper aims to:

1. Analyzing Drone-Related Incidents and Their Associated Challenges
2. Exploration of Techniques for UAV Detection and Identification
3. Assessment of Advantages and Limitations of UAV Detection Approaches
4. Investigating the Impact of RF Fingerprinting on Improving UAV Detection and Identification

The present paper also assesses the important advancements in technology alongside drone encounters, sharing incidents from the real world to highlight their security threats. It analyzes different methods of UAV detection while mentioning their pros and cons. In addition, the paper deals with the problems that separate sensor mechanisms have to deal with due to interference from the environment or overlapping operations. Thus, it advocates for the need to employ integrated detection approaches as a solution for such challenges. All in all, this application aims to provide the reader with important details and information related to the current scenario and future trends and approaches in UAV detection and identification technologies.

1.1 UAV Detection and Its Importance: Responding to Drone-Related Incidents

Drones are being utilized for a variety of non-military means, including smart agriculture. It has become crucial that drones be effectively detected and identified in order to prevent illegal activities as the variety of their uses globally increases. This study has been conducted due to the rudimentary challenges posed by the rapid increase in the use of helicopters and UAVs all over the world, as well as location privacy, security, and public safety. This is important because it presents a timely examination and evaluation of the latest drone detection technologies meant for the protection of national sovereignty and personal and public safety. Drones are constructed with several parts, like GPS equipment, infrared cameras, batteries, and sensors. High-energy batteries, including lithium-ion batteries, are used to limit the flying time from 20 to 40 minutes. It is possible to acquire commercially available drones weighing approximately USD 1000, which can hover in the air for around 30 minutes and travel several kilometers. Such a low cost makes it easy for malicious parties to use such items to transport explosives or toxic chemicals in addition to using them to spy on or gather information from their targets [4]. As a result, drones that are capable of long-range flight with heavy payloads have the potential to be used to transport hazardous materials while remaining impervious to wind and harsh weather.

As reported by news agencies, drone activities have caused disruption to the public as well as many institutions, and one of the reports suggests the drone incident at Gatwick Airport in 2018 did indeed cause an airport to cease operations and result in the loss of major revenue for airlines and airports. Furthermore, the drone incidents have posed a risk to the air force, who had the difficult task of neutralizing them; it was too dangerous to shoot the drones down due to the risk of bullets hitting civilians or nearby buildings. Wearing a device was suggested as an alternative, but tracking the source turned too complicated [5]. So, as far as the drones were concerned, striking targets had much better prospects. One more report notes that drones are being enlisted during armed conflicts, with a notable incident being the Jammu Air Base in India on the 27th of June, 2021, when drones utilizing improvised explosive devices attacked various targets near the India-Pakistan border, the said airbase being one of those targets. The Border Security Force (BSF) of India, tasked with securing the Indian side of the international border, has reported a significant increase in drone sightings during 2022.

Comparing this to the previous years, there exists a notable increase, with over 268 instances against 109 and 49 in 2021 and 2020, respectively. Hence, the rise in the use of drones indicates a new strategy development on the part of Pakistan since it uses drones as a new gadget in the ongoing border conflict with India [6]. A report states that an Italian prisoner shot some of the rival inmates with a pistol that had allegedly been brought into the prison by a drone [7]. Various drone accidents that happened in the years 2023 and 2024 are shown in Fig. 1 and Fig. 2.

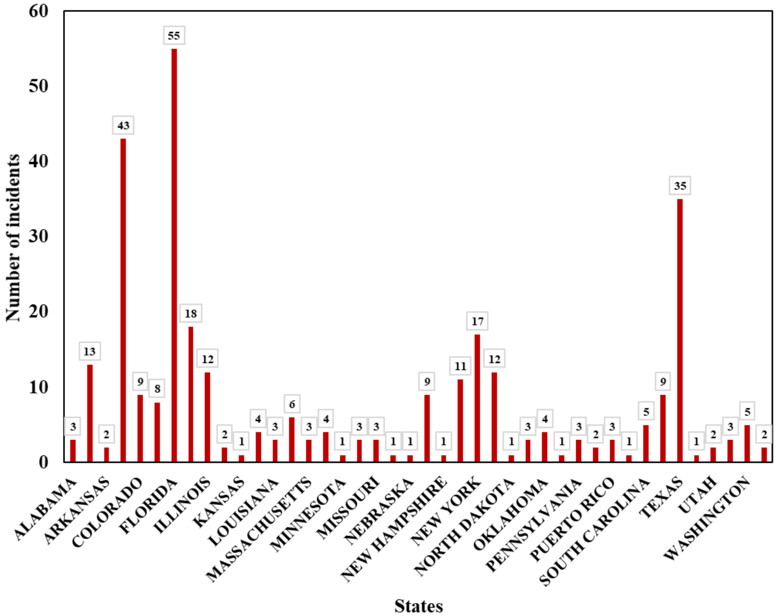

Fig. 1. Recorded drone incidents from January to March 2024.

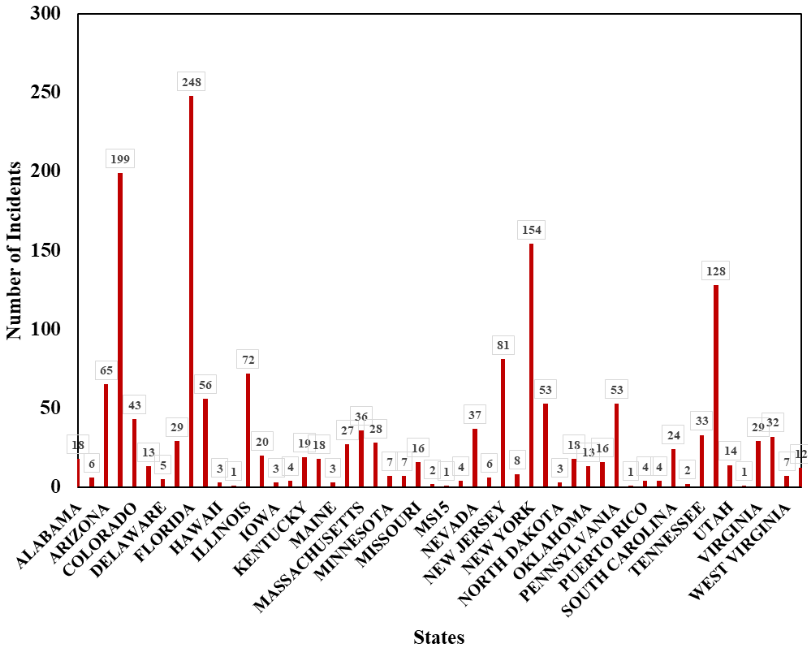

Fig. 2. Recorded drone incidents from January to December 2023.

1.2. Challenges Associated to UAV Threats and Risks

Indeed, the wide nexus of drone use—the use of drones—introduces a range of various technical and/or security and/or public safety challenges that require some form of regulations or mechanisms to be put in place. The increasing availability of the drones has raised concerns over privacy, security, and the safety of the public to a greater extent. It is absolutely possible that the use of cameras mounted on drones would constitute a serious invasion of privacy and be used to spy on individuals or their property without proper consent. Additionally, drones can be put to wrongful use to carry out drug and weapon smuggling across borders or into restricted areas, which is a serious threat to the public [8].

Moreover, drone usage within the vicinity of essential assets, including electrical wires and telecommunication systems, can cause jamming effects or even damage, subsequently hampering operations or resulting in accidents. In the most extreme situations, drones have been deployed to inflict damage by dropping explosives or toxic materials, which can endanger lives and compromise public safety [9]. There is a need to detect these problems and put in place regulatory measures to deal with unauthorized drone use to reduce the threats they pose [3]. A few of these challenges are depicted in Fig. 3.

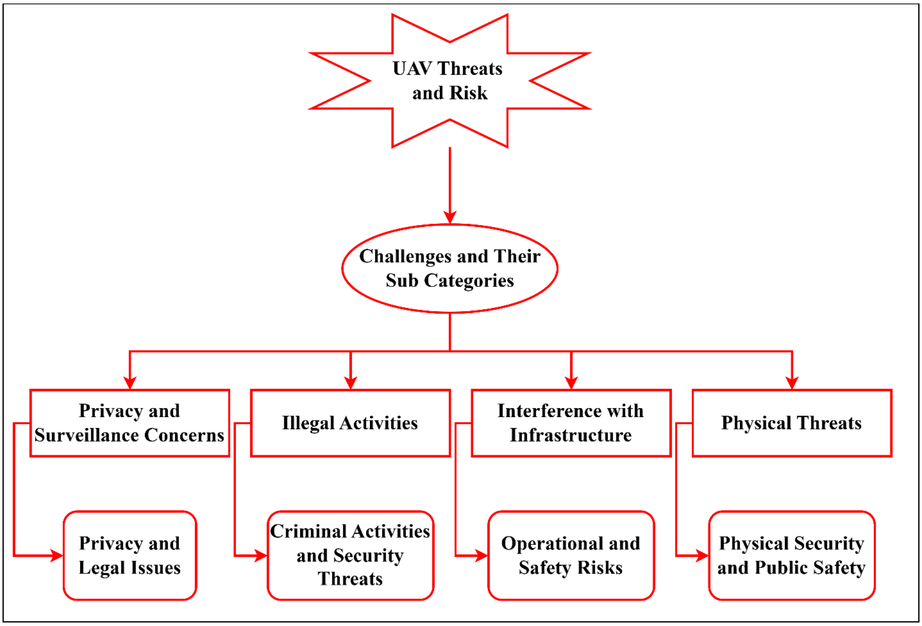

Fig. 3. UAVs Threats and Risks

2. UAV Detection Methods

In the field of drone detection, researchers are continuously exploring various techniques outlined in literature to improve their accuracy. These methods include utilizing audio, video, radar, and RF sensors. The focus is on optimizing these approaches to better identify and monitor drones, highlighting the significance of innovative solutions to counter the evolving threats posed by unmanned aerial vehicles. Table 1 compares the advantages and limitations of available detection methods [8, 9, 23].

Table 1. Comparison among various drone detection techniques.

Detection Technology	Detection Principle	Advantages	Limitations
Radar	Utilizes radio waves for detection	Long-range capabilities, operates in all weather conditions	High cost, potential for false alarms in cluttered environments
Acoustic Sensing	Detects drones based on sound emissions	360-degree coverage, cost-effective solution	Limited detection range, impacted by other sounds in noisy environments
Visual Recognition	Identifies drones using visual cues	High accuracy, real-time detection	Performance affected by lighting conditions (Required good lightning conditions), limited effectiveness in complex environments
RF- Sensing	Detects drones through RF emissions	Versatile applicability, effective in cluttered environments	Susceptible to interference, limited range

2.1. Radar Detection

Using radar for drone detection involves emitting radio waves into the airspace and analyzing the reflections to identify objects, including drones. Radar systems transmit radio waves, usually within the microwave frequency range, and capture the reflections or echoes from objects in the airspace [21]. Signal processing algorithms then analyze these reflections to differentiate between various objects and track their movement over time. Radar-based detection provides advantages such as long-range capability and the ability to detect drones beyond line-of-sight. However, it may struggle with detecting small drones with low radar cross-sections and may require additional sensor fusion or classification techniques for precise identification [24]. The systems utilizing radars are also wired to face challenges, as it is common for their detection capabilities to be compromised by environmental conditions like humidity, clouds, and dust [25]. Radar technology, which employs the detection of back-scattered electromagnetic signals, is the most sophisticated and expensive of all established technologies to locate drones. Nonetheless, it needs a strong active beam to ensure long-range coverage, and the use of radar close to airfields may be restricted due to ultimate licensing. In spite of these limitations, radar is reliable for monitoring multiple targets in an area and can function regardless of the weather. Tracking small drones, low altitudes, slow speeds, and urban settings severely impacts the accuracy of passive radar, making it a prospective option.

2.1.1. Acoustic Detection

Audio detection depends on picking up the noise generated by the motors of a drone. Designed sound detectors are used to identify these sound signatures created by the spinning motion of the drone motor. This approach offers a signal within the specified detection distance. Has two main drawbacks. Firstly, its detection range typically falls under 300 meters. In places with lots of noise, like bustling cities or industrial zones, the sound detector might struggle to pick up the drone's noise over all the background sounds accurately. This highlights the importance of using detection techniques to make sure drone detection systems are thorough and precise [24]. The emergence of drones has posed a challenge for acoustic detection methods to identify them correctly [25].

2.1.2. Visual Detection

The process of video detection includes examining images or particular items recorded by cameras. The benefit of this method lies in its detection abilities compared to other techniques. However, it faces difficulties when birds or other airborne objects come into the field of view of the video detector. Moreover, deterioration in visibility due to factors like weather conditions or dim lighting can impede the efficiency of the detection process. The importance of algorithms and additional detection methods becomes evident when facing these obstacles to accurately identify and detect drones across environmental scenarios [24]. Lighting and weather conditions significantly impact visual detection approaches, posing challenges in drone spotting [25]. Table 2 summarizes the previous work using radar, audio, and visual sensing-based techniques.

Table 2. Summary of work Related to Detection & Identification of drones Based on radar, acoustic, and visual detection techniques.

Ref.	Methodology	Data set	Findings
[10]	An X-Band radar system used that operates at a frequency of approximately 10.5 GHz	Data were collected through the developed radar system, which can function in either data gathering mode or target detection mode.	SAD (Sum of absolute differences) gives the best result in matching among other four algorithms, and correctly identification is done by using radar system.
[11]	K-Band FMCW radar prototype	Data were collected using Arcade PICO Drone Nano Quadcopter	By using K-Band FMCW Using a radar system, nano-drones can be identified, and their micro-Doppler signatures can be obtained through a Short-Time Fourier Transform (STFT).
[12]	It uses a chirp-pulse radar system for detecting drones by examining target fluctuation models. This approach leverages radar cross-section (RCS) measurements to determine the characteristics and movement of drones.	includes drone flight experiments or radar measurements focused on capturing drone movement patterns.	The study's findings emphasize the capability of chirp-pulse radar to identify drones. particularly through the use of target fluctuation models, enhancing drone identification accuracy under various conditions.

Ref.	Methodology	Data set	Findings
[13]	It utilizes a chirp-pulse Doppler monostatic radar operating at a frequency range of 34.5 GHz to detect drones. The system utilizes three different pulse modes to address the ambiguity issue in pulse compression radar and measures the radar cross-section (RCS) of drones.	On a river-side road in Daejeon, Measurements were obtained from a field test conducted on a straight segment of a Korea. Two scenarios were evaluated: a flying drone and a stationary drone.	The system successfully detected the movement of drones, both flying and stationary, including the detection of drone blades' radar cross-section (RCS). Vertically fixed drones' detectability was superior to that of horizontally fixed drones due to the rapid fluctuation in the RCS caused by rotating blades.
[14]	Conducted drone detection using transformed data analyzed through two distinct methods: plotted images and ML techniques, specifically SVM and KNN.	-------	PIL method Achieved 83% accuracy over the KNN.
[15]	Developed a multimodal UAV 3D trajectory exposure system (MUTES) that fuses optical sensor and acoustic systems.	Data were collected by field experiments using microphone array-Based acoustic approach. The drone audio dataset is used.	MUTES provides wide-range detection (90° to 360°) and high-precision 3D tracking for UAVs.
[16]	Trained a CNN on audio recordings of drones for classification.	Diverse drone audio samples and background noises.	Achieved high detection accuracy, demonstrating the system's effectiveness in distinguishing drone sounds from environmental noise.
[17]	Proposed a combination of visible, thermal, and acoustic, multi-sensor system for real-time drone tracking and detection.	The dataset comprises various drone scenarios with recordings from thermal, visible and acoustic sensors in different environmental conditions.	The multi-sensor system significantly improves detection accuracy and tracking reliability compared to single-sensor approaches, demonstrating effectiveness in diverse operational settings.
[18]	Integrating deep learning methods with optical sensing to developed a system for drone tracking, detection, and identification.	Data set were collected with the field experiments.	This proposed approach exhibited outstanding accuracy and precision compared to existing methods.
[19]	The object detection methods chosen for investigation in this study include YOLOv5 and YOLOv8 key one-stage detectors and Retina-net, as well as Faster R-CNN.	Utilized datasets included the complex background dataset , sky background dataset, and rainy test set, sourced from publicly available collections.	YOLOv8 showed improved performance on the sky background dataset (SBD), while YOLOv5 outperformed YOLOv8 on the complex background dataset (CBD).
[20]	Yolov5 algorithm that uses deep conventional neural network (cnn) with pytorch Framework.	6820 images were collected from google, roboflow, Instagram, etc.	The YOLOv5 model achieves higher accuracy while maintaining a fast detection speed.

2.2. RF Sensing-Based Detection

The fundamental concept behind Radio Frequency (RF) detection is to identify the presence of a drone by detecting the RF communication signal between the drone and its remote controller. Drones generally operate within specific frequency bands, so once these bands are identified, it suggests the potential presence of a drone within the detection area.

However, it's important to note that the presence of an RF signal does not necessarily confirm that a drone is present, as other wireless technologies, like Wi-Fi, also operate within the same frequency band. To improve detection accuracy, an advanced method can focus on specific RF signal characteristics, particularly for drones that use Wi-Fi protocols and Media Access Control (MAC) addresses. The advantage of the RF detection method is its capability to identify any drone operating within the scanned frequency range [24]. RF analysis offers a high degree of accuracy in detecting drones, and in some cases, it can even identify the specific drone's make and model. This method works by analyzing the radio frequencies that drones use to communicate with their controllers. By studying these signals, it becomes possible to recognize patterns and unique characteristics that help pinpoint the type of drone being used [25]. Passive Radio Frequency (RF) sensing is regarded as one of the most effective methods for civilian drone detection. This technique operates on the principle that the drone communicates wirelessly with its controller. It does not require special licenses and is capable of detecting multiple drones in various weather conditions and at any time of day. With a basic antenna, the detection range can extend over one kilometer, and with more advanced equipment, it can reach distances beyond ten kilometers [26]. The main advantage of RF sensors is that they do not radiate power, enabling them to detect a longer range. They are particularly useful when combined with counter-UAV measures like jamming. In practice, RF sensors can apply various types of analysis to the captured RF signals, which makes them even more powerful in detecting and countering threats. One of the best features of RF sensors is that the receiver can be connected directly to a jammer, allowing immediate and automated countermeasures when the signals are detected. [23].

2.3. Drone Detection and Identification based on RF Fingerprint

Unmanned Air Vehicle detection and identification using RF signals can be divided into two main types: those based on the physical features of the RF signal and those based on the MAC layer's features. Usually, these methods involve using a device that can sense RF signals to capture the signals between a UAV and its controller. By analyzing different aspects of the RF signal, like its strength or frequency, patterns unique to different types of UAVs and how they operate can be identified. In our work, we will use an RF physical layer features-based technique to detect and identify UAVs, also known as drones [27]. This unique radio frequency fingerprint is distinct from other wireless communication technologies like Wireless Local Area Networks (WLAN) and Bluetooth. While WLAN and Bluetooth also use radio waves to transmit data, each has its own specific characteristics and protocols. For example, WLAN operates on different frequency bands and follows specific standards like Wi-Fi, while Bluetooth uses a frequency-hopping spread spectrum to avoid interference. These differences in frequency bands, modulation techniques, and protocols ensure that the RF fingerprint of a drone's transmission is unique and distinguishable from other types of wireless communication [22]. Table 3, shown below, summarizes the previous work done by using RF with the fingerprint technique.

Table 3. Summary of work Related to Detection & Identification of drones Based on RF Fingerprint Sensing Technique.

Ref.	Technique	Classes	Data	Classifier	Results
[23]	RF signals	three models of multi-channel 1DCNN	DroneRF	1DCNN Models	First Model Accuracy: 100%, Second model accuracy:94.6%, and third model accuracy: 87.4%.
[24]	RF Sensing	NA	Captured RF signals in real-time	NA	drones can be detected on maximum 12 m distance
[25]	RF signals	2 classes (RF Background and RF communication)	DroneRF	CNN	Achieved F1 score and accuracy exceeding 99.7%, while drone identification reaches F1 score and accuracy of 88.4%.
[26]	RF signals	1 Class	Data is collected locally by capturing the signal and generating a real-time spectrogram within the SDR platform using hardware acceleration.	1DCNN & 2DCNN	The final signal detection performance showed an SNR margin of -8.7 dB, with drone identification achieved accuracy 99.93% in simulations. 150 meters and 350 meter 99.4% and 99.38% accuracy achieved in Real-life experiments.
[27]	RF signals	3 classes	RF signal Data captured	FEG and MC-DNN	Proposed method outperforms with accuracy 98.4% and F1 score 98.3%
[28]	RF fingerprints	3 classes	Proposed naïve byes decision mechanism based on Markov model.	CNN	Achieved accuracy in between 92%-100% for an SNR range from 10db-30db.
[29]	RF Fingerprints	10-class	Drone RF dataset is collected through 9 commercial drones and one Wi-Fi signal.	Proposed new deep residual neural network.	Achieved an accuracy of 99% for both single and simultaneous classification method for multi-drone.
[22]	Passive Radio-Frequency with RF Fingerprint	3 classes	Captured RF data through 17 UAV controller, 6 Bluetooth devices and one Wi-Fi router.	5 ML algorithms	KNN classifier gives 98.13% accuracy
[30]	RF Fingerprint	---------	RF signals captured by GNU radio and STFT is used for its time-frequency-energy distribution.	Featured were extracted by PCA and fed into classification algorithms SVM, KNN, MLP	Highest accuracy achieved by Multilayer Perceptron algorithm 99.99%.

3. Discussion

The proliferation of drones has intensified concerns about security, privacy, and safety, highlighting the urgent need for effective UAV detection techniques. A review of existing UAV detection techniques reveals the complexities involved in identifying and classifying drones within real-world environments. While radar detection methods have their strengths and weaknesses, as do visual approaches, in dealing with obstacles like buildings and noise in settings, RF-based detection methods stand out for their reliability, especially when combined with RF fingerprint analysis to offer a more resilient solution to track and recognize drones using their communication signals, like Wi-Fi and Bluetooth, even in demanding cityscapes. While RF methods might face some challenges, with interference issues along the way, the distinct features identified through RF fingerprinting boost the accuracy and dependability of detection efforts. This combination doesn't just address interference problems. Also strengthens the ability to identify objects, highlighting RF fingerprinting's importance in UAV detection systems development. As drone technology advances further, fine-tuning these combined approaches will play a role in managing the growing complexities brought by UAV presence in different industries.

4. Conclusion and Future Scope

The widespread use of UAVs creates issues in privacy and safety that need to be addressed, making detection and identification systems necessary. One of the approaches that have been used for detection is RF-based techniques, which have shown potential when combined with RF fingerprint technology to address these challenges effectively in places where considerable signal overlap is available or in a dense urban environment. Common approaches for object identification, including radar, acoustic, visual, and others, are often limited by nearby interference from buildings, lighting, or specifically environmental noise. At the same time, RF-based detection enables a more consistent identification solution. RF fingerprinting, an additional level of granularity, results in RF features typical of every specific drone signal being gathered, improving UAV detection and providing additional granularity for practical sensing of UAVs. Going forward, future work must focus on delivering the next generation of RF systems, which will require greater immunity to interference and greater complexity of urban environments. These efforts will aid in creating common frameworks and extensive databases for RF fingerprinting across a wide variety of UAV models and environments, which are key to developing scalable and effective detection systems. With the increased development and widespread interest in drone technology, their best use for security will depend upon these integrated detection strategies, playing an enormous key in enhancing security while also addressing privacy concerns, making them crucial and invaluable assets for both public and private domain spaces, especially at a time when UAV Technology is booming.

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