RF-Based Drone Detection using AI Models: Results, Trends, and Open Issues

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***Abstract*—This study explores various AI models for RF-based drone detection and surveillance. Both quality and quantitative analyses of extant literature are carried out. The preliminary review results hint that Deep Learning (DL) approaches provides greater detection accuracy than other AI models. The consistent reinvention of the current enabling technologies will guarantee the solution to inherent and emerging issues in drone detection and surveillance as well as provide a road-map for future work.**

***Index Terms*—Artificial intelligence, Detection, Drone, Radio Frequency, Security, UAV.**

I. Introduction

Nowadays, several industries and scenarios have enjoyed the advancement of drone technology. However, this advancement comes with security and safety concerns [1]. Recently, drones are now employed to violate restricted areas. One such illegal activity/ drone attack is the drone attack on Saudi Arabia's oilfield that led to significant economic loss for the country [1]. Thus, averting such acts executed by drone usage is vital for the safety of our world. Drone detection systems (otherwise known as anti-drone systems) designed to prevent drone incursions need to cope with future drone technology to sustain emerging drone transportation systems (DTS).

Existing drone detection methods based on acoustics, radar, and vision deployed in drone surveillance systems have limitations. In the acoustic detection method, the Direction of Arrival (DOA) coming from the drone's propeller is used to localize audio using the time-frequency feature of the drone. However, its drawback is the sensitivity to noise, limiting it to locations with ambient noises that will interfere with the drone's acoustic signal [2]. Radar systems operate by emitting radio frequency waves. The signal is reflected off the surface of the drone and then captured by radar [3]. Radar's disadvantage is its inability to detect small drones and its high sensitivity to noise. However, the radio frequency (RF) approach outperforms the other detection methods. Some vendors prefer to use multiple RF scanners for drone detection because they are less expensive than radar systems with equivalent coverage. It also enables longer-range detection.

Artificial Intelligence (AI) has become an enabler for drone detection and classification [4]. Researchers currently leverage Deep Learning (DL) and Machine Learning (ML), as they appear to outperform others. This work aims to accessing the performance of various AI models used by RF-technique in drone detection by anti-drone surveillance systems.

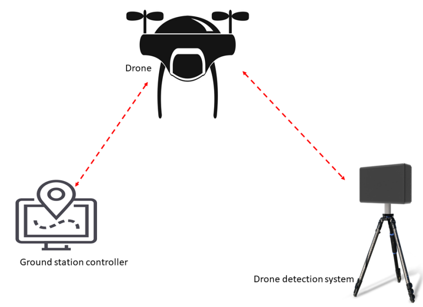

Fig. 1. RF-Based Drone Detection showing RF Signals Processing

II. Methodology and Review Approach

This study followed the PRISMA (preferred reporting items for systematic reviews and meta-analyses) methodology. The following search terms were employed in this review: "RF", "Drone", "Detection", and "AI". The following databases are used to collect articles: IEEE Xplore, ResearchGate, Datascience Google scholar, and ACM digital libraries. Following the first search through five databases and other sources, 41 documents were obtained. Due to duplication, 8 of these documents were excluded. Eight more documents were rejected after being screened for relevance. Following that, 7 articles were ruled ineligible. The remaining 17 documents were screened and divided into 12 for qualitative analysis and 6 for quantitative analysis [5].

III. Results and Discussions

In the RF-based detection approach, an RF signal is continuously sent via a transmitter and a reflected signal from a drone is received [6]. It monitors existing signals before isolating and analyzing them with a receiver. The shortcoming of the RF-based approach is its inability to detect autonomous drones. Most AI models for RF-based drone detection are usually DL [7] due to their ability to generate precise predictions from large amounts of unlabeled and unstructured data. This is unlike the ML model that is used for drone classification and is limited to supervised learning of structured and labeled data. In [8], a multi-tasking learning neural network (MTLNN) was proposed for RF-based detection and classification, leveraging on convolution layers for multiple task performance and cross-entropy loss function for optimization. This model gave 100% accuracy with detection and 96% for classification. To achieve

TABLE I
PROSPECTS AND OPEN ISSUES IN RF-BASED DETECTION

Ref.No.	Model	Prospects	Open issues
[7]	Blockchain technology	Enhance network security	Safety of data, data leakage issues
[8]	Explainable AI	Unbox and simplify detection process	Still an emerging area, codified issues
[12]	Federated learning	Efficient resource usage	Data privacy, Data access right and Data Diversity
[13]	Self-supervised learning	Cognition in detection	Detection on a large scale with high uncertainty
[14]	Reinforcement learning	Non-human intervention in detection	High sensitivity to hyper-parameter choices,the simulation-reality gap

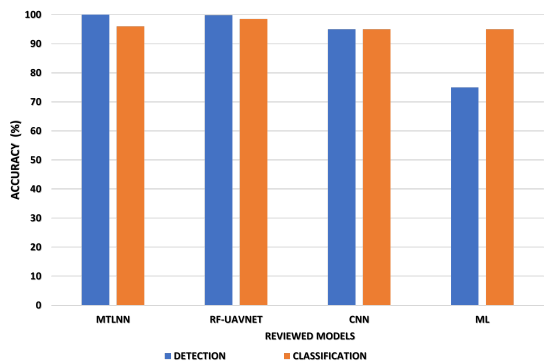

Fig. 2. Detection and Classification Accuracy Performance of existing Models

cost efficiency, authors [9] developed a lightweight RF-based detection model (RF-UAVNET) with a multi-level skipped connection network that achieved a high detection and classification performance for operation mode recognition. Similarly, authors [10] proposed a lightweight convolution neural network (CNN) with several one-dimensional layers to successively learn the different scales feature map of radio frequency signals, collected from 17 drones. The model achieved a detection accuracy of 95%, and sensitivity of 95% across the different drones. Finally, authors [11] proposed an ML approach that used the identified unique signatures of WiFi devices in terms of RF and network packet measurement to distinguish the presence of WiFi drones and standard WiFi devices in an urban setting. This achieved 75% detection accuracy and 90% classification accuracy. These results are a clear indication of the superior capability of AI models in handling emerging RF-based drone detection problems irrespective of their dynamics and sophistication

IV. Conclusion

This paper reviewed different AI models deployed for RF-based drone detection and classification. Prediction results show that the DL model had better detection performance than the ML models. It also offered future research direction on open issues associated with RF-based drone detection for the improvement of the anti-drone system's sophistication in task performance.

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