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AI-assisted frequency-modulated continuous wave radar for drone detection near runways: Challenges, trends, and research gaps

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ABSTRACT

Unmanned aerial vehicles (UAVs), birds, and foreign objects near airport runways pose a serious threat to aviation safety, particularly during takeoff and landing phases, when aircraft operate at high speeds and low altitudes. Although drone-related incidents remain infrequent, they can cause significant disruptions, including costly flight delays and safety concerns. This paper presents a focused review of drone detection techniques, emphasizing the integration of frequency-modulated continuous wave (FMCW) radar and artificial intelligence methods – fespecially convolutional neural networks – for UAV detection near runways. The article highlights the key benefits and limitations of these approaches in low-altitude, cluttered environments typical of airport infrastructure. Particular attention is given to the role of digital signal processing, including the use of short-time Fourier transform for extracting micro-Doppler signatures from radar echoes, which are subsequently analyzed by deep learning models. The review also outlines current research gaps, including the lack of real-world data and scenario-specific studies. The aim is to support the development of reliable UAV detection systems tailored to the unique challenges of runway surveillance.

Keywords: UAV detection, runway intrusion, FMCW radar, convolutional neural networks, micro-Doppler, airport security, artificial intelligence.

INTRODUCTION

In recent years, artificial intelligence (AI) has gained increasing attention, becoming a vital component in numerous domains of modern life. One of its most dynamic branches is machine learning (ML), particularly deep learning, which builds upon classical neural network models. Deep neural networks (DNNs) have demonstrated remarkable performance not only in image analysis but also in audio, speech, and text processing tasks [1]. These models have found practical applications across various sectors, including autonomous vehicles [2], healthcare [3], robotics [4], and agriculture [5]. A prominent example of AI's capabilities is the transformer-based language model ChatGPT, which illustrates the potential of large neural architectures in human–machine interaction and decision-making [6].

AI also plays an increasingly significant role in aviation, especially in the development and deployment of UAVs, currently the fastest-growing segment of the global aerospace industry [7]. Although UAVs contribute to diverse areas of society, they also pose notable risks, such as unauthorized airspace intrusion [8], potential use in criminal or terrorist activities [9], and collision threats to crewed aircraft and critical infrastructure [10].

While no fatal drone incidents have been officially reported, documented collisions and near-misses have forced emergency landings, often resulting from operator error, technical faults, or unstable communication links [7]. Research conducted at the University of Dayton and Cranfield University demonstrated that UAVs can severely damage aircraft radars, with battery ignition adding further hazards [7]. Studies by the Federal Aviation Administration (FAA) under the Alliance for System Safety of UAS through Research Excellence (ASSURE) program revealed that drones cause more structural damage than birds of similar mass, especially to wings and stabilizers [7]. In 2023, drones were involved in 18% of reported aviation incidents near runways [11]. Dublin Airport recorded the highest number of such events, while in the UK and USA, thousands of passengers experienced delays due to drones – primarily DJI Mavic 2, Phantom 4, and Mavic 3 models. At Warsaw Chopin Airport, a drone of considerable size passed within 30 meters of a landing LOT aircraft, causing a 30-minute suspension of runway operations [7].

These incidents emphasize the urgent need for advanced UAV detection and classification systems capable of identifying drone presence, position, and flight parameters in real time. Effective detection remains challenging due to UAVs' small physical dimensions, low-altitude operation, and limited radar cross-section, which make them difficult to track using conventional radar systems. As violations of restricted airspace become more frequent, especially around airports, developing reliable detection solutions has become a critical priority for regulatory bodies, security services, and aviation authorities. This paper reviews recent advancements in UAV detection based on AI, with a particular focus on FMCW radar and CNNs. It also highlights key UAV-related risks, analyzes real-world incident reports, and identifies research gaps that require further investigation.

DRONE DETECTION METHODS

Contemporary research on drone detection and classification explores a variety of sensor-based methods, each characterized by unique capabilities and limitations. The most commonly used techniques include radar-based, radio-frequency (RF)-based, acoustic, and vision-based approaches. In recent years, researchers have increasingly integrated these with AI classifiers such as Support Vector Machines (SVMs) [12–13] and CNNs to improve the accuracy, automation, and real-time performance of UAV detection systems.

Although a wide range of detection techniques is available and frequently combined in multi-sensor systems, the remainder of this article focuses exclusively on radar-based methods. This decision aligns with the scope of the study and reflects the growing significance of radar technology – particularly FMCW radar – in AI-supported UAV detection, especially in the context of airport runway surveillance. The following sections explore radar signal characteristics, challenges related to low radar cross-section (RCS) targets, and the application of deep learning models such as CNNs to radar data processing.

Radar-based systems, particularly those using FMCW radars, detect UAVs by analyzing radio wave reflections to estimate object distance, velocity, and micro-Doppler signatures generated by drone propellers [14]. These systems operate effectively in various weather conditions and are capable of detecting and tracking objects over long distances. However, detecting small UAVs remains challenging due to their low RCS, and false positives are common, especially in the presence of birds or other small airborne objects [15]. Additionally, micro-Doppler signal processing requires substantial computational resources.

RF-based detection methods analyze communication signals exchanged between UAVs and their ground controllers, identifying distinct frequency patterns and transmission protocols [16]. These systems can detect drones at long ranges and may even locate the operator's position. Nevertheless, they are ineffective against fully autonomous UAVs that operate without active transmissions and are susceptible to interference from other RF sources, such as Wi-Fi or cellular networks [17].

Acoustic detection relies on the identification of characteristic sound signatures produced by drone propellers and motors [18]. This method is particularly useful in environments where RF signals are absent or obstructed. Despite its relatively low deployment cost, acoustic detection suffers from a short effective range (typically under 500 meters) and reduced performance in noisy environments, especially urban or windy areas [19].

Vision-based systems utilize high-resolution optical sensors combined with computer vision algorithms to detect and classify UAVs based on visual cues [20]. These systems, often enhanced by deep learning models such as you only look once (YOLO) or CNNs, can distinguish between different drone types and provide visual confirmation of intrusions. However, their effectiveness is heavily dependent on favorable environmental conditions, requiring a clear line of sight and sufficient lighting [21].

To overcome the limitations of single-sensor systems, modern approaches increasingly adopt multi-sensor data fusion. These architectures integrate data from multiple modalities—such as radar and optical cameras, or RF and acoustic sensors—to create more robust and reliable detection pipelines [22]. AI-based fusion models leverage either feature-level or decision-level fusion techniques to correlate complementary data streams and increase detection confidence. For example, vision data can be used to validate radar detections, while RF signals can assist in narrowing down regions of interest for visual tracking. Such systems are particularly promising in airport environments, where low-flying UAVs may be obscured by infrastructure, weather conditions can change rapidly, and real-time decision-making is crucial [23].

The increasing complexity of UAV behavior and the evolution of counter-detection tactics demand flexible, adaptive, and intelligent surveillance solutions. Therefore, integrating multiple sensing modalities with machine learning algorithms remains a key direction in the development of next-generation UAV detection and classification systems.

Radar-based methods

Radar-based UAV detection systems are valued for their ability to operate in adverse weather and lighting conditions, as well as for their effectiveness in long-range surveillance. However, challenges remain in distinguishing UAVs from other airborne objects, particularly birds, and in the need for advanced signal analysis and classification algorithms.

A key phenomenon supporting radar-based classification is the micro-Doppler effect, which arises from radar wave modulation by moving parts of a target, such as drone propellers or human limbs [24]. Unlike conventional radar features such as radar cross-section (RCS) or translational velocity, micro-Doppler provides additional motion-based information derived from rotating components [25]. This can significantly enhance the ability to detect and classify UAVs. Figure 1 illustrates a typical micro-Doppler signature of a moving human forearm [24].

In UAV detection, this effect manifests clearly due to the high-frequency rotation of drone propellers. Figure 2 shows a representative micro-Doppler signature generated by a two-blade rotor on a model helicopter [24].

Growing interest in this effect has led to numerous studies exploring its utility in UAV classification. For instance, researchers in [26] developed a method for identifying small drones based on their propeller-induced micro-Doppler patterns. In [27], the micro-Doppler signatures of three drone models and four bird species were compared using phase-coherent radar operating in the K-band (24 GHz) and W-band (94 GHz), revealing significant distinctions that support the efficacy of such radars in drone detection.

Another study [28] employed a custom continuous-wave radar at 10 GHz to collect micro-Doppler data for various UAVs and birds. The researchers used support vector machines (SVMs) to classify drone size, distinguish drones from birds, and perform multi-class classification across five object categories. Although the

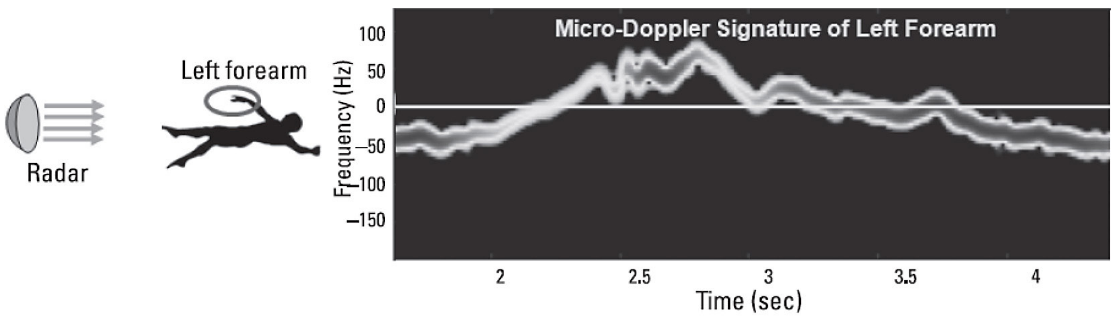

Figure 1. The micro-Doppler signature of the left forearm [24]

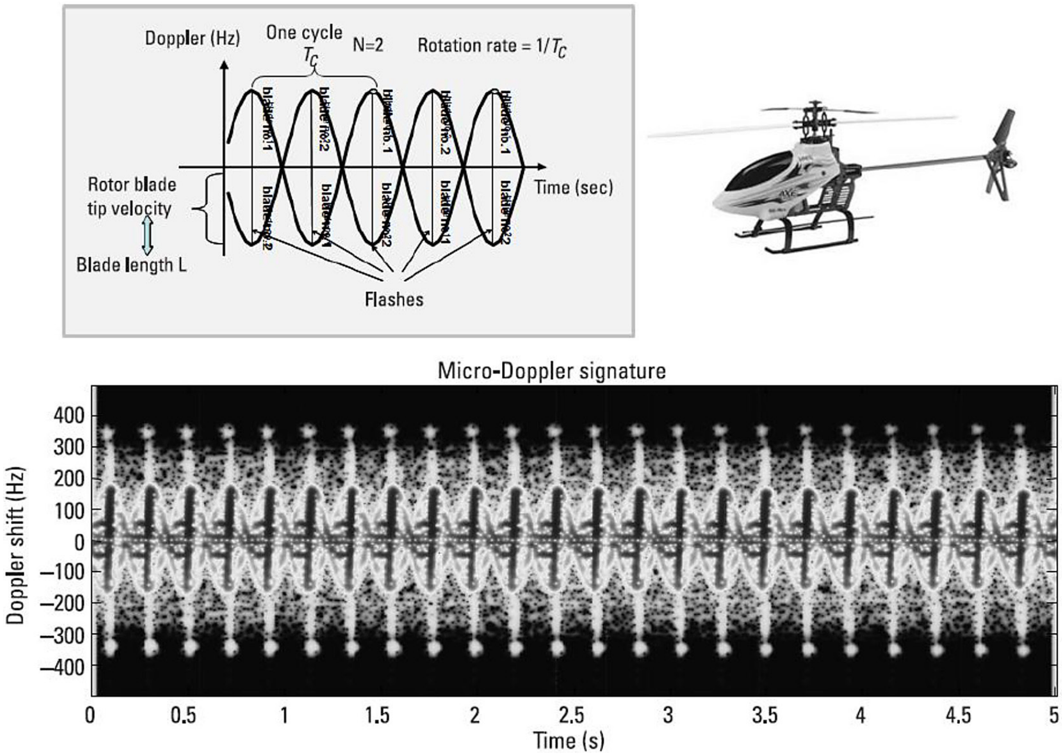

Figure 2. The micro-Doppler signature of a rotor with two blades on a model helicopter [24]

experimental setup was constrained by limited data collection conditions, the results underscore the potential of micro-Doppler-based approaches. A more detailed discussion of the FMCW radar and CNN-based detection framework is presented in the following sections.

APPLICATION OF FMCW RADAR AND CONVOLUTIONAL NEURAL NETWORKS IN UAV DETECTION NEAR AIRPORT RUNWAYS

Despite extensive research into UAV detection using radar and artificial intelligence, the specific problem of drone detection over airport runways remains insufficiently addressed in the literature. Most existing studies focus on general environments such as open fields, urban areas, or simulation test beds, with limited consideration of the operational constraints, spatial dynamics, and safety-critical nature of runway zones. To the best of the authors' knowledge, no published work proposes or evaluates an AI-assisted radar system specifically configured for real-time UAV detection at the runway threshold.

To address this gap, a detection scenario tailored for low-altitude UAV incursions near the end of an airport runway is introduced. The system employs two FMCW radar units placed symmetrically at the runway threshold, each with a 100-meter detection range and a 30° azimuth and elevation field of view. The proposed deployment is illustrated in Figure 3.

This configuration enables continuous monitoring of the immediate airspace corridor where UAV intrusions pose the highest operational risk. Importantly, due to their relatively low transmission power and narrow operational bandwidth, FMCW radars of this type do not interfere with airport navigation aids, such as instrument landing systems (ILS), nor with primary and secondary surveillance radars used in air traffic control.

The radar parameters used in this scenario are based on the uRAD USB v1.2 module – a 24 GHz FMCW radar developed by Anteral – which the authors have utilized in their earlier research. This device is compact, USB-powered, and supports real-time streaming of radar data (I/Q components), making it suitable for integration into mobile or stationary surveillance systems.

Based on this spatial setup, the system utilizes artificial intelligence techniques to classify radar returns in real time. The full processing pipeline is shown in Figure 4. Radar echoes from the

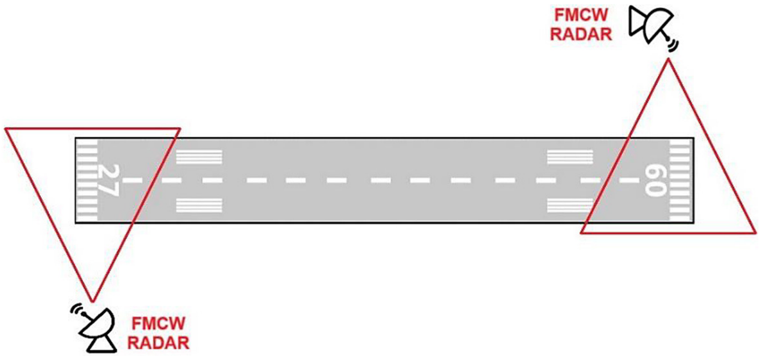

Figure 3. Proposed placement of dual FMCW radar units at the runway threshold, showing coverage zone for low-altitude UAV detection

UAV are captured through a USB interface and processed to extract the in-phase (I) and quadrature (Q) signal components. Using STFT, a time-frequency spectrogram is generated. This spectrogram is then analyzed by a pre-trained CNN, which classifies the object into its respective UAV category based on its micro-Doppler signature.

FMCW radar

FMCW radar combines the advantages of pulsed and continuous wave systems, enabling the simultaneous measurement of radial velocity, angular position, and range to a target by linearly modulating the frequency of the transmitted signal over time [29].

FMCW radar offers several benefits, including low transmitted power, compact design, and relatively simple construction due to the absence of high-power switches and synchronizing components typical of pulsed systems. Its ability to continuously transmit and receive radio waves allows for real-time tracking of moving objects at short to medium ranges, making it well-suited for UAV detection in constrained environments such as airport runways. A typical block diagram of an FMCW radar system is presented in Figure 5.

In this architecture, the transmitted signal is divided using a directional coupler. One portion is radiated via the transmitting antenna, while the other serves as a local oscillator (LO) reference in the receiving path. The reflected echo signal is captured by the receiving antenna, amplified, and mixed with the LO signal in a nonlinear mixer. This produces sum and difference frequency components; a low-pass filter removes the high-frequency component, yielding the intermediate frequency (IF) signal [29].

The IF signal undergoes quadrature demodulation and analog-to-digital conversion, producing

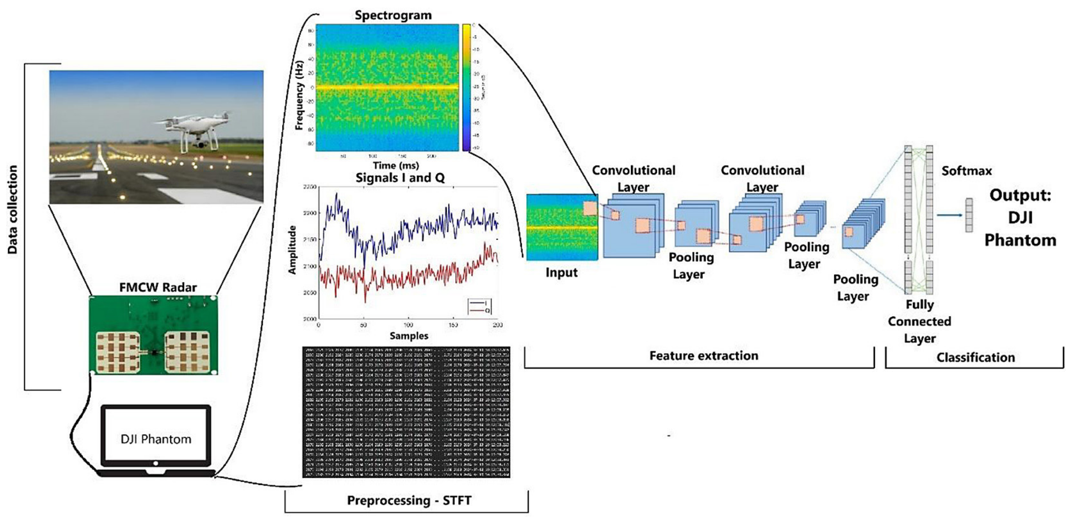

Figure 4. Data flow in the drone detection and identification method using FMCW radar, STFT processing, and CNN

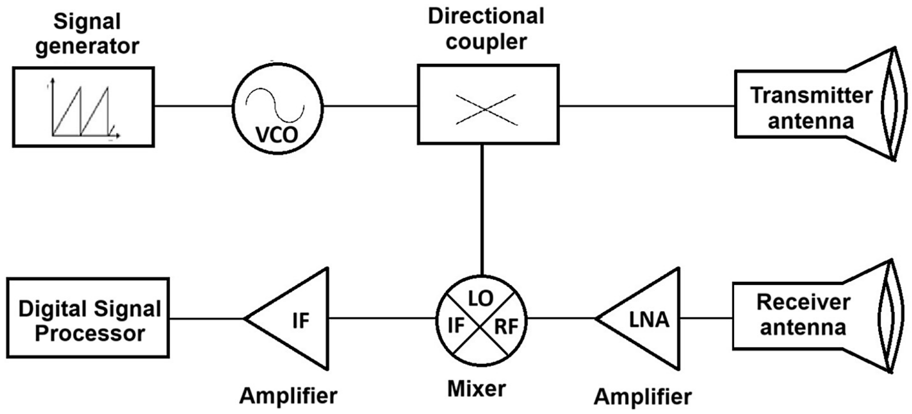

Figure 5. Block diagram of FMCW radar

complex I/Q data for further analysis. Signal processing techniques such as STFT Gabor Transform, Wavelet Transform, or Wigner-Ville Distribution can be applied to extract meaningful features—most notably, micro-Doppler signatures. Target detection is typically performed using threshold-based methods or adaptive techniques such as the constant false alarm rate (CFAR) algorithm [30].

The FMCW radar transmits an electromagnetic signal with time-varying frequency. In the context of this article, sawtooth frequency modulation is considered as a representative waveform, as illustrated in Figure 6. This type of modulation, characterized by a linear frequency increase followed by an instantaneous reset, is commonly used in FMCW radar systems due to its implementation simplicity and efficient range measurement capability [31]. The unidirectional frequency sweep allows for continuous range tracking with lower hardware complexity compared to symmetric waveforms. Although sawtooth modulation may introduce Doppler ambiguity in velocity estimation for moving targets, it remains suitable for many practical detection scenarios, including UAV detection at short ranges, where range resolution and processing speed are prioritized over exact Doppler discrimination.

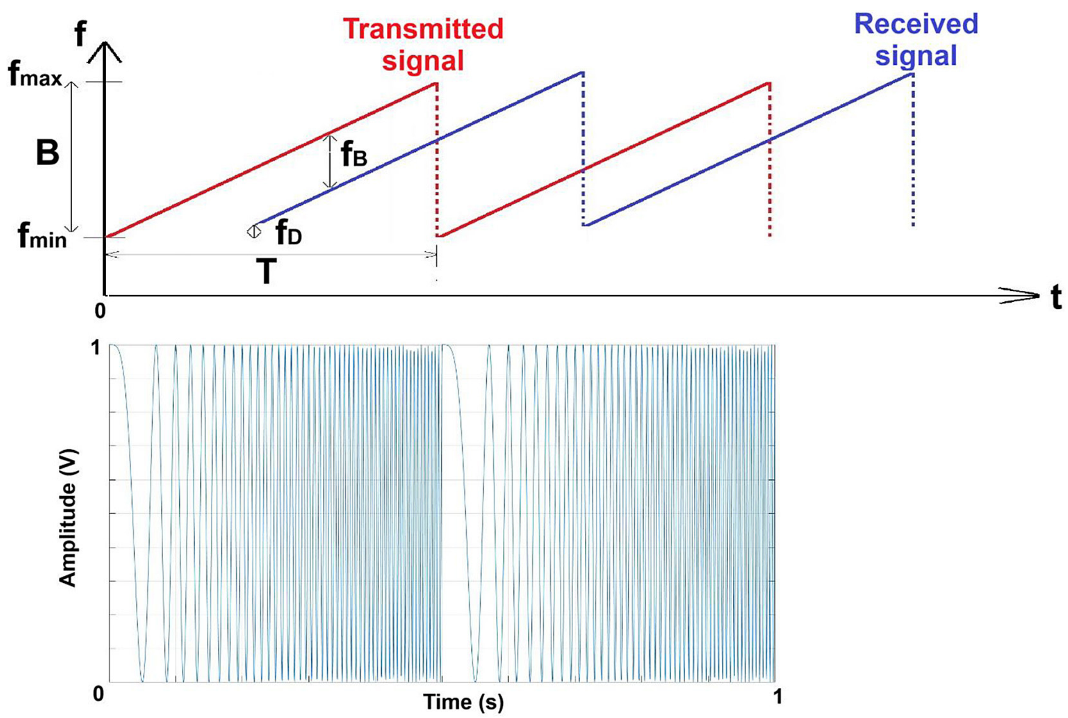

Figure 6. Linear frequency modulation signal

The sawtooth signal with frequency modulation transmitted by an FMCW radar can be mathematically modeled as [29]:

$$s(t) = \cos\big(2\pi f_C t + \varphi(t)\big) \quad (1)$$

where: f_c the frequency of operation of a radar system, $\varphi(t)$ denotes phase which can be modeled as [29]:

$$\varphi(t) = \pi k \beta T^2 + \pi \beta t^2 \quad (2)$$

where: $k = 0,...,K\text{-}1$, t denotes the time variable, T is the sweep period of the sawtooth modulation and coefficient β is given by the relationship:

$$\beta = \frac{B}{T} \quad (3)$$

B denotes the bandwidth, defined as the difference between the maximum frequency f_{max} and the minimum frequency f_{min}:

$$B = f_{max} - f_{min} \quad (4)$$

When the transmitted signal encounters an object, a portion of the electromagnetic wave's energy reflects back to the radar. After passing through the receiver path, the signal takes the form [29]:

$$y(t) \approx \varepsilon e^{-j2\pi f_B t} e^{-j2\pi f_D kT} \quad (5)$$

where: ε represents a complex coefficient dependent on the antenna gain, f_B represents the frequency difference between the transmitted signal and the echo, f_D represents the Doppler frequency. If the object reflecting the signal is stationary, the reflected wave will have the same frequency as the transmitted signal. However, when the object is in motion, the frequency of the reflected wave shifts by a value f_D, which depends on the object's velocity in the direction of the radar. This velocity is called radial velocity, representing the component of the object's motion directed toward or away from the radar. Knowing the values of f_B and f_D, the velocity and distance to the object can be determined accordingly [29]:

$$V = \frac{f_D c}{2 f_c} \quad (6)$$

$$R = \frac{f_B c}{2\beta} \quad (7)$$

where: c denotes velocity of light.

While FMCW radar offers significant advantages – such as low power consumption, compact design, and the ability to simultaneously measure range and velocity – it also presents several limitations. Its range resolution is constrained by the bandwidth of the transmitted signal, requiring wideband operation for fine detail detection. Additionally, velocity estimation can suffer from Doppler ambiguities, especially in unidirectional (e.g., sawtooth) modulation schemes. Multipath effects in cluttered environments, such as those found near runways, may introduce signal artifacts or false detections. Finally, the performance of FMCW systems in detecting low-RCS targets such as small UAVs remains a challenge, particularly at greater distances or in the presence of environmental noise and interference [30].

Short time Fourier transform

The STFT is a commonly used technique for analyzing non-stationary radar signals, such as those influenced by the micro-Doppler effect. Unlike stationary signals with constant spectral content, non-stationary signals exhibit time-varying frequency components. STFT enables time–frequency representation by dividing the signal into short overlapping segments (windows) and applying the Fourier transform to each segment individually [32].

This process produces a two-dimensional representation called a spectrogram, defined as the squared magnitude of the STFT. Spectrograms reveal the temporal evolution of spectral components, making them especially useful for detecting motion-induced features in radar echoes—such as those caused by drone propellers. These visual time–frequency patterns serve as suitable input for CNNs in classification tasks [12].

The continuous and discrete forms of the STFT are expressed by the following equations [32]:

$$X(t,f) = \int_{-\infty}^{\infty} x(\tau) w(\tau - t) e^{-j2\pi f t} d\tau \quad (8)$$

$$X(n,m) = \frac{1}{N} \sum_{k=-\infty}^{\infty} x(k) w(k-n) e^{-j2\pi \frac{mk}{N}} \quad (9)$$

where: $x(\tau)$ represents the analyzed signal in the time domain, and $w(\tau - t)$ denotes the time window that moves along the signal $x(\tau)$, $x(k)$ represents the sequence of discrete signal samples, N denotes the frame length, n indicates the position of the frame along the analyzed signal and m

= 0,1,2,…,N-1 represents the time shift. The most commonly used window functions include Hanning, Hamming, Kaiser, and Blackman windows.

For the short-time Fourier transform, the spectrogram is defined as the square of its magnitude[32]:

$$S(t, f) = |X(t, f)|^2 \tag{10}$$

An example of an STFT applied to a linearly modulated frequency signal (LFM) is presented in Figure 7.

While the STFT is widely used in radar signal analysis due to its simplicity and compatibility with spectrogram-based classification, it suffers from a fundamental limitation: fixed time-frequency resolution, which restricts its adaptability to signals with varying dynamics. To overcome this, alternative time–frequency transforms have been explored in recent studies on UAV detection and micro-Doppler analysis [32].

One such method is the Wavelet Transform, which provides multi-resolution analysis by adapting the window size to different frequency components [12]. It offers better time resolution for high-frequency events and better frequency resolution for low-frequency components, making it particularly effective for detecting short, transient features in radar echoes.

Another approach is the Wigner-Ville Distribution, known for its excellent time-frequency resolution [32]. However, its practical application is limited by the presence of interference artifacts known as "cross-terms", which reduce interpretability, especially in multi-component signals like those reflected from drones. The Gabor Transform represents a refinement of STFT using a Gaussian window function, achieving a more optimal balance between time and frequency resolution. While it shares some limitations of STFT, it provides improved performance in applications involving periodic or slowly varying signals [32].

More advanced and adaptive techniques include the Hilbert-Huang transform (HHT), which decomposes the signal into intrinsic mode functions using empirical mode decomposition. This method is highly effective for non-linear and non-stationary signals but suffers from high computational complexity and instability in certain signal conditions [32]. Finally, the Chirplet Transform extends wavelet analysis by introducing chirp-like basis functions, making it well-suited for analyzing frequency-modulated signals such as those affected by micro-Doppler. Though computationally demanding, it provides enhanced sensitivity to the frequency variation patterns typical of drone propellers [32].

Although STFT remains the most commonly used tool due to its computational efficiency and simplicity, alternative transforms such as wavelet or chirplet methods may offer improved performance for specific signal types. The choice of transform should be guided by the signal characteristics, detection requirements, and computational constraints of the system.

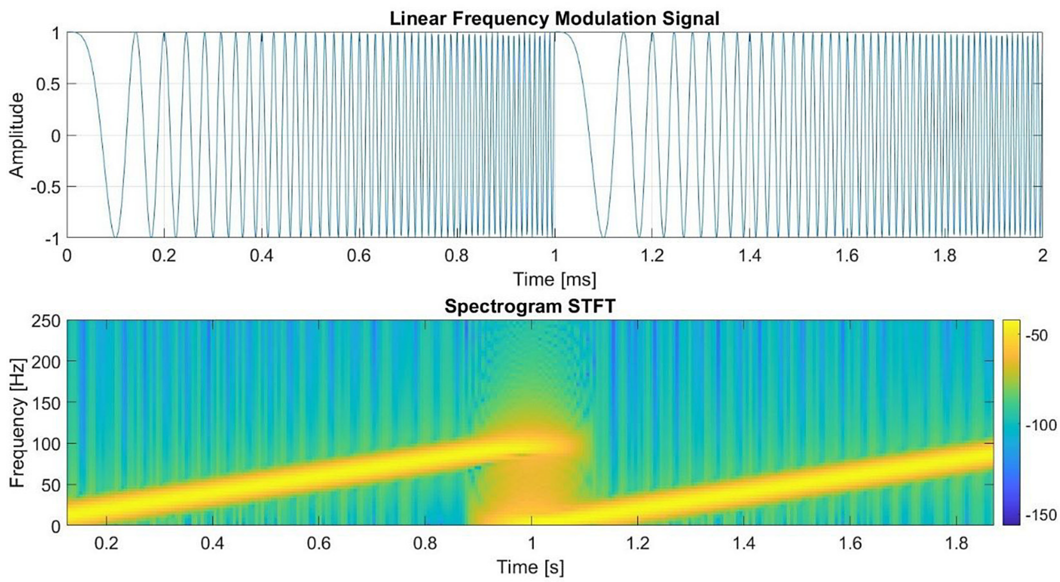

Figure 7. Example of a short-time Fourier t+6ransform for a LFM signal

Convolutional neural network

Convolutional neural networks (CNNs) are widely used in signal analysis, including radar and acoustic domains, due to their ability to automatically extract spatial and temporal features from time–frequency data such as spectrograms [33]. This makes them particularly effective for classifying micro-Doppler signatures generated by UAVs. Figure 8 shows an example of a typical CNN architecture.

CNNs operate hierarchically, where early convolutional layers detect simple features (e.g., edges), and deeper layers capture more abstract patterns. Filters extract local features, activation functions like ReLU introduce non-linearity, and pooling layers reduce dimensionality while enhancing robustness [34]. Batch normalization is often applied to stabilize and accelerate training [35].

The learning process is based on minimizing a loss function using optimizers such as Adam, which dynamically adjusts learning rates for different weights, improving convergence under varying gradient conditions [33]. Learning rate schedules are also used to improve fine-tuning, applying higher rates at early stages and decreasing them as training progresses [36].

Additional techniques such as data augmentation enhance generalization, especially when training data is limited. Transfer learning with pre-trained models (e.g., ImageNet) allows reuse of learned features, reducing training time and improving accuracy in domain-specific tasks. Ensemble learning, which combines outputs of multiple models, further improves classification robustness [33].

CNN-based models are evaluated using metrics such as accuracy, recall, and specificity, with additional tools like ROC-AUC and the confusion matrix providing deeper insights into class separability and error types [33]. Standard practice includes splitting data into training, validation, and test sets, with final model performance assessed exclusively on the test set to prevent overfitting [34]. Cross-validation and repeated testing across multiple data splits help improve reliability and account for variability in results [35].

BACKGROUND

Numerous studies have investigated the use of AI techniques in combination with radar signal processing for the detection and classification of UAVs. In particular, the integration of FMCW radar, STFT for micro-Doppler analysis, and deep learning methods such as CNNs has shown promising results in terms of detection accuracy and robustness in non-cooperative scenarios.

A comprehensive summary of recent studies applying FMCW radar, digital signal processing techniques, and AI-based classifiers for UAV detection is presented in Table 1.

In [37], a CNN-based approach was proposed for classifying UAVs, humans, and vehicles using raw range-time data from a compact FMCW radar with a range of up to 30 meters. The radar signals were processed into log-scaled mel-spectrograms via STFT and analyzed using a 6-layer CNN, achieving only 32.1% accuracy for UAVs, mainly due to their low radar cross-section. The dataset comprised 1,937 samples, augmented to 3,944 using standard techniques. Despite demonstrating the feasibility of CNNs for radar signal classification, the study lacked information on radar frequency, UAV models, and real-world testing conditions, limiting its practical applicability to environments like airport runways.

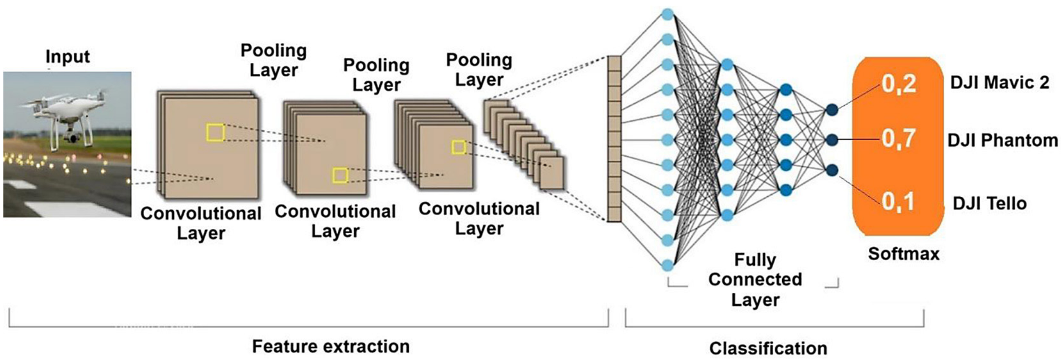

Figure 8. Example of a CNN network structure

Table 1. The latest research on drone detection using FMCW radar and artificial intelligence.

Reference (Year)	Radar frequency	Detected drones	DSP methods	Classifier	Dataset info	Accuracy/results
[37] 2019	Not specified	Unspecified UAV	STFT + Mel-spectrogram	6-layer CNN	1,937 samples (aug. to 3,944)	32.1% UAV accuracy
[38] 2021	X-band (8–12 GHz)	Metafly, Mavic Air 2, Disco	STFT	ResNet-18, ResNet-SP	18 variants/sample, not public	83.4% (ResNet-SP)
[39] 2021	mmWave (76–79 GHz)	Single UAV type (not named)	1D FFT + Custom micro-Doppler	Custom CNN, LightGBM	400 TFIs (2 classes)	95% (custom CNN)
[40] 2022	X-band (9.6 GHz)	Multiple simulated drones	STFT + ZAM transform	CNN (custom)	Synthetic TF images	Up to 100% (simulated)
[41] 2022)	77 GHz	DJI Mavic 2, Matrice 200, Phantom 3	Fourier-based transform + normalization	5-layer CNN	Public dataset (Zenodo)	95% (known), 86% (OOD)
[42] 2022)	K-band (23.8 GHz)	DJI Mavic Air 2, Inspire 2, SJRC	STFT + range–time fusion + amplitude	Modified multi-scale	Custom dataset (indoor/outdoor), range ≤12 m	Outperformed AlexNet (+9.4%) and VGG16
[43] (2023)	77 GHz	DJI Mavic Mini 2, RadioFLY	MTI filter + micro-Doppler	Custom CNN	136 real, 32,000 synthetic	78.68% (model-based CNN)
[44] (2024)	24 GHz	DJI Inspire 2, Phantom 4 Pro, Mavic 2 Pro	Range–Doppler images + overlay	AlexNet, GoogLeNet, SqueezeNet	3600 images/class	99.96% (GoogLeNet)

Park et al. [38] proposed a CNN-based classification approach for UAV detection using micro-Doppler signatures extracted from FMCW radar signals. An Ancortek SDR-KIT 980AD2 radar operating in the X-band (8–12 GHz) was used to record echoes from five low-RCS targets, including three UAVs (Metafly – wing-flapping, Mavic Air 2 – quadcopter, and Disco – fixed-wing) and two human activities (walking and sit-walking). The radar data were transformed into spectrogram images using short-time Fourier transform (STFT), with various window sizes (128, 256, 512) and overlap ratios (50–85%) to capture temporal and spectral features.

A total of 18 spectrogram variants per sample were generated through augmentation (e.g., vertical flips) and used to train two models: ResNet-18 and a lightweight custom variant, ResNet-SP. The latter achieved 83.4% accuracy and outperformed ResNet-18 (79.9%) with reduced training time (242 s vs. 640 s), showing better efficiency for real-time applications. The authors highlighted the importance of preserving real and imaginary parts of the radar signal for optimal learning. Additional techniques included anomaly filtering and gradient clipping to stabilize training. The radar data were collected within a range of 100 meters, but the dataset was not made publicly available. Limitations included constrained UAV movement scenarios and limited radar visibility for fast or low-RCS UAVs like the Disco model.

Rai et al. [39] proposed a method for drone localization and activity classification using mmWave FMCW radar (76–79 GHz, 4 GHz bandwidth) with 3 TX and 4 RX antennas, oriented vertically to estimate elevation angle and localize the UAV from a ground station. A small commercial drone (322 × 242 × 84 mm) was used as the target, detectable up to ~10 meters. Signal processing involved range estimation via 1D FFT and micro-Doppler signature extraction through a custom 2D FFT-based algorithm. For classification, they built a dataset of 400 time-frequency images (rotating vs. non-rotating UAV), evaluated on multiple ML models: logistic regression, SVM, LightGBM (93% accuracy), and a custom lightweight CNN that achieved 95% accuracy, outperforming larger pre-trained models (e.g., ResNet50, InceptionResNet). The custom CNN was optimized for edge devices due to its low complexity (~93,000 parameters, ~1MB size). Limitations included short detection range and a binary activity classification (only rotating vs. not rotating), leaving room for expanding UAV types and behaviors.

In [40], Yoon et al. proposed an efficient protocol for classifying multiple UAVs and birds using FMCW radar operating at 9.6 GHz (X-band). The study relied on simulated micro-Doppler signatures and employed short-time Fourier transform (STFT) and the Zao–Atlas–Marks (ZAM) transform, a high-resolution time–frequency analysis method that enhances the visibility of

Doppler modulations caused by moving targets. These time–frequency representations were used to train CNN classifiers to distinguish between combinations of 1–2 drones and 1–2 birds. Among the three evaluated protocols, the most realistic setup achieved up to 100% classification accuracy under favorable conditions (clutter-to-signal ratio ≥ 15 dB).

Despite excellent performance in simulation, the study lacked real radar data and faced challenges in distinguishing scenarios with similar Doppler patterns (e.g., 2 vs. 3 drones), highlighting the need for real-world datasets and adaptive training strategies.

In [41], Karlsson et al. proposed a CNN-based method for drone classification using data from a 77 GHz FMCW radar (SAAB SIRS 1600) with 160 MHz bandwidth and 1 m range resolution. The radar captured micro-Doppler signals from six drone models (e.g., DJI Matrice 200 V2, Mavic 2 Pro, Phantom 3), as well as birds, humans, and passive reflectors. Each data sample included five range bins collected over a 9 ms dwell time. The digital signal processing (DSP) pipeline consisted of Fourier-based transformations and amplitude normalization to ensure uniform signal-to-noise ratio across inputs. A 5-layer CNN was trained using the Adam optimizer. To improve robustness against out-of-distribution (OOD) drones, synthetic data generated from a mathematical propeller motion model was incorporated into training. This led to an increase in classification accuracy from 78% to 86% for unknown drones, and up to 95% for known drone classes at SNR > 17.5 dB. The authors emphasized the challenges of class generalization and short dwell times, proposing synthetic augmentation and convolutional filter analysis as strategies for improving interpretability and robustness.

In [42], a method was proposed to classify five rotary-wing drones (including DJI Mavic Air 2, Inspire 2, and SJRC S70 W) and birds (bionic and seagull) using K-band FMCW radar operating at 23.8 GHz. The radar captured micro-Doppler (m-D) signatures under various conditions (indoor and outdoor, distances up to 12 m). A novel dataset was constructed by combining time-frequency (T-F) spectrograms with range–time plots and applying custom data augmentation via display amplitude modulation and feature fusion. The signals were processed with STFT, and a modified multi-scale CNN was trained, outperforming baseline models like AlexNet and VGG16 by 9.4% and 4.6% respectively. The study emphasized the value of range–time and m-D fusion for robust classification and addressed dataset scarcity, but was limited to short-range measurements and a fixed set of UAV and bird types.

In [43], the authors proposed a model-based data augmentation technique to improve drone classification using a 77 GHz FMCW MIMO (Multiple-Input, Multiple-Output) radar system. The study aimed to classify UAVs based on the number of rotors, comparing quadcopters (DJI Mavic Mini 2) and single-engine helicopters (RadioFLY). Instead of relying solely on costly and time-consuming measurements, a deterministic physical model was used to synthetically generate micro-Doppler radar signatures for UAVs, allowing efficient dataset creation. The authors applied a moving target indicator (MTI) filter to extract range profiles and used 400-point data vectors as CNN input. The best performance (78.68% accuracy) was achieved with the CNN trained on model-augmented data (σP = 0.20), significantly outperforming a conventional signal augmentation approach (66.18%), which also showed a strong bias. The dataset used included real measurements (136 signatures) and 32.000 synthetic samples. The approach enabled high-fidelity classification without extensive real-world measurements, highlighting a key advantage for scalable UAV detection research. However, the method did not incorporate angular features from MIMO processing, and the classification task was limited to only two UAV types.

In [44], the authors proposed a novel drone detection method using overlaid range–Doppler maps generated by a 24 GHz FMCW radar (Eval-DEMORAD). Three DJI drones (Inspire 2, Phantom 4 Pro, Mavic 2 Pro) were detected at distances between 2 and 12 meters. The digital signal processing (DSP) relied on conventional range–Doppler image generation, enhanced through an image overlay technique that accumulates micro-Doppler signatures (MDS) from multiple frames. This approach significantly improved classification performance using CNN architectures including AlexNet, GoogLeNet, and SqueezeNet. The dataset consisted of 3600 images per drone type, with 600 overlaid images generated from six-frame sequences. The best results were achieved with GoogLeNet, reaching 99.96% accuracy for drone detection, outperforming both standard CNN and SVM baselines. The study highlighted that even small and distant drones could be effectively detected, although limitations included a maximum test distance of 12 m and reliance on proprietary image data instead of raw radar signals.

CONCLUSIONS

This paper presents a novel approach for detecting UAVs near airport runways using FMCW radar, time-frequency signal analysis, and AI-based classification methods. The review of recent studies demonstrates a variety of approaches to UAV detection, each with its strengths and limitations.

In comparison to previous methods, the integration of FMCW radar with CNNs for classification offers several advantages, particularly in terms of cost-effectiveness and compactness. While traditional radar systems often struggle with multipath effects and detecting small, low-RCS drones at long distances, FMCW radar is able to detect UAVs at relatively shorter ranges, especially when combined with advanced signal processing techniques such as STFT and micro-Doppler signature extraction.

Among the reviewed approaches, CNN-based methods demonstrate significant potential for UAV classification in radar signals. However, the performance of these systems heavily depends on the quality and size of the training datasets. Studies have shown promising results with CNN architectures such as ResNet-18 and custom lightweight models, which outperform traditional models in terms of both accuracy and training time. However, these methods face challenges related to real-world applicability, such as limited training data, constrained UAV movement scenarios, and radar visibility issues, particularly for fast-moving or low-RCS drones.

In terms of signal processing, the use of STFT has proven effective for generating time-frequency representations of radar signals, but it suffers from fixed time-frequency resolution. As noted in several studies, the adoption of more adaptive transforms, such as wavelets or chirplets, may improve the detection capabilities by providing better time-frequency localization. For example, the use of wavelet transforms could potentially offer more flexibility in analyzing UAVs with rapidly changing Doppler signatures.

Alternative radar architectures, such as MIMO and SAR (synthetic aperture radar), offer promising directions for future research. MIMO radar, with its ability to transmit and receive multiple signals simultaneously, can improve range resolution and accuracy, making it suitable for detecting small UAVs at longer distances. SAR, on the other hand, offers high-resolution imaging that can be useful for identifying objects, including drones, in complex environments. The combination of FMCW radar with MIMO or SAR technologies could significantly enhance UAV detection capabilities, especially in challenging environments like airport runways, where precise detection and localization are critical. Future research directions include:

- developing publicly available datasets based on real FMCW radar measurements in airport environments, which would help improve the performance of ai models;
- optimizing lightweight and interpretable ai models for deployment in edge or onboard devices, making them more suitable for real-time applications;
- exploring multimodal sensor fusion, combining radar with visual or rf sensors, to increase robustness and accuracy in detection systems;
- investigating the use of MIMO and SAR radar architectures to further enhance detection capabilities, especially for small, low-RCS UAVs at longer ranges;
- validating the entire detection pipeline in real operational conditions at airports to ensure the feasibility and reliability of the proposed solution. this targeted approach may significantly enhance the safety of air operations in light of the increasing threat posed by UAV incursions.

By addressing these challenges and exploring these future research directions, this work aims to significantly enhance the safety of air operations, especially as the threat posed by UAV incursions continues to grow.

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