Radar Spectrum Analysis and Machine Learning-Based Classification for Identity-Based Unmanned Aerial Vehicles Detection and Authentication

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***Abstract*—The significant use of Unmanned Aerial Vehicles (UAVs) in commercial and civilian applications presents various cybersecurity challenges, particularly in detection and authentication. Unauthorized UAVs can be very harmful to the people on the ground, the infrastructure, the right to privacy, and other UAVs. Moreover, using the internet for UAV communication may expose authorized ones to attacks, causing a loss of confidentiality, integrity, and information availability. This paper introduces radar-based UAV detection and authentication using Micro-Doppler (MD) signal analysis. The study provides a unique dataset comprising radar signals from three distinct UAV models captured under varying operational conditions. The dataset enables the analysis of specific features and classification through machine learning models, including k-nearest Neighbor (k-NN), Random Forest, and Support Vector Machine (SVM). The approach leverages radar signal processing to extract MD signatures for accurate UAV identification, enhancing detection and authentication processes. The result indicates that Random Forest achieved the highest accuracy of 100%, with high classification accuracy and zero false alarms, demonstrating its suitability for real-time monitoring. This also highlights the potential of radar-based MD analysis for UAV detection, and it establishes a foundational approach for developing robust UAV monitoring systems, with potential applications in aviation military surveillance, public safety, and regulatory compliance. Future work will focus on expanding the dataset and integrating Remote Identification (RID) policy. A policy that mandates UAVs to disclose their identity upon approaching any territory, this will help to enhance security and scalability of the system.**

Keywords*—*Authentication; detection; cybersecurity; Micro-Doppler; radar; Unmanned Aerial Vehicle (UAV)

I. Introduction

Unmanned Aerial Vehicles (UAVs) are rapidly gaining momentum across various sectors where information technology is crucial in enhancing efficiency and operations [1]. The popularity of UAVs is due to their cost-effectiveness, ease of use, and potential to streamline business processes [1]. UAVs are being deployed in various industries, including transportation, agriculture, surveillance, and defense, offering unprecedented flexibility and operational efficiency. However, this widespread adoption is not without challenges, as UAVs increasingly face cybersecurity threats. These threats pose risks to the integrity of UAV operations and the safety of the data they collect and transmit [2].

Cybersecurity is critical for the safe operation of UAVs. A breach in security can endanger ground personnel, infrastructure, personal privacy, and the UAVs themselves. Since UAVs rely heavily on internet connectivity, they are vulnerable to threats compromising confidentiality, integrity, and availability [3]. Confidentiality may be violated through data interception, physical tampering, eavesdropping, or social engineering attacks. Integrity is at risk from data tampering and hacking, while availability can be disrupted by interference, jamming, denial-of-service attacks, or natural events [3].

UAV detection is identifying and tracking UAVs using various technologies, such as radar, cameras, or acoustic sensors among others. It plays a crucial role in ensuring the safety and security of airspace by monitoring unauthorized and potentially harmful UAV activity. The detection and classification of UAVs can be challenging, and various technological approaches offer unique advantages and limitations [4].

1) Radar detection: This approach works by emitting radio waves (signals) that reflect off UAVs, allowing it to gather detailed information about the UAV's distance, speed, and movement patterns [4]. Radar's ability to operate in all weather conditions and low-visibility environments, such as during rain, fog, or nighttime, makes it highly reliable [8]. It is particularly effective for long-range detection and can differentiate UAVs from other objects by analyzing their motion and size. This robustness and capability to detect small UAVs over large distances make radar an essential tool in security-critical environments [5].

2) Video detection: It relies on cameras and image processing algorithms to visually identify UAVs. It excels in clear visibility conditions, offering high-resolution images for accurate UAV identification and classification [4]. Video detection can work in real time, leveraging machine learning to enhance accuracy. However, its effectiveness diminishes in poor lighting conditions, such as nighttime or foggy environments, and it struggles to detect small UAVs at long distances [5]. Consequently, while video detection is valuable in specific contexts, its dependence on favorable visibility limits its reliability.

3) Acoustic detection: It captures the unique sound signatures produced by UAVs, especially the noise from their propellers and motors [4]. The method uses microphones to monitor sound and can detect UAVs even when they are not visible. Acoustic detection is a cost-effective and straightforward solution for short-range detection, in quiet environments [5]. However, its range is limited, and it faces significant challenges in noisy environments, such as urban areas. In addition, it struggles to detect noiseless UAV models, making it less effective for comprehensive UAV detection over larger areas.

4) RF-Based detection: It monitors the communication signals transmitted between UAVs and their controllers [4]. This method is highly effective for detecting UAVs as soon as they begin transmitting signals, and it can provide valuable information about both the UAV and its operator [5]. However, RF-based detection is ineffective against fully autonomous UAVs that do not rely on RF signals or operate with encrypted communications. Moreover, its range is limited to the transmission distance of the UAV's signals, and it can be vulnerable to signal interference or jamming, reducing its reliability [5].

Among these methods, radar-based UAV detection is effective as it captures unique MD signatures generated by a UAV's rotating blades and motion. The radar signals analysis can detect, classify, and track UAVs in low visibility conditions, providing valuable information for security, surveillance, and air traffic management [5], [6]. Radar detection is preferred for its versatility and reliability. Unlike video, acoustic, or RF-based detection, radar is unaffected by visibility, background noise, or signal dependence. Its ability to detect UAVs over long distances and in all weather, conditions make it the most robust solution for UAV detection, in security and defense applications where continuous and reliable monitoring is essential [5], [6], [7]. Despites the radar's effectiveness, the existing systems struggle to identify specific UAV types using MD features or radar cross-section (RCS) characteristics. Furthermore, reliance on proprietary datasets limits the generalizability of findings and hinders benchmarking efforts. This shows the need for standard, and public available datasets to improve radar-based detection and authentication methods.

In light of this, this research focuses on developing an identity-based UAV detection and authentication system that leverages information on radar signal analysis. The system uses radar to analyze the UAV's signal through the MD effect, which reveals unique features of the UAV's rotor movements and structure. These unique MD radar features will help to authenticate the UAV's identity, ensuring that it matches the information and parameters of the known UAVs. Then, the proposed system employs the k-NN, Random Forest, and SVM to classify and authenticate UAVs based on the identified patterns in radar signal data. Furthermore, this research generates raw datasets for three distinct UAV models: DJI Matrice 600, DJI Matrice 300, and Phantom 4. The study offers an identity-based UAV detection, authentication, and classification model. The model handles detection and authentication in separate phases, while the combined model integrates both processes into a unified approach. The proposed model is compared with others to ascertain its efficiency and performance. This comparison underscores the advantages and limitations of each framework, demonstrating their applicability in real-world scenarios.

The research makes stride contributions to the field of UAV detection, classification, and authentication. These contributions include a novel radar-based dataset, generated through simulations of three UAV models (DJI Matrice 600, DJI Matrice 300, and Phantom 4), that can provide a foundation for advanced research in this domain. The study also develops a robust classification system employing machine learning algorithms (kNN, Random Forest, and SVM). The proposed model effectively detects and classifies UAVs and enhances authentication by comparing radar signal data with predefined UAV parameters. Furthermore, the performance of the proposed models is evaluated on the radar dataset, demonstrating improved detection accuracy and reliable classification and authentication.

B. Our Contributions

This research offers the following contributions:

1) A novel radar-based dataset is created through simulation using three UAV models (DJI Matrice 600, DJI Matrice 300, and Phantom 4). This dataset will be instrumental for future UAV detection, authentication, and classification research.

2) A classification system is developed using kNN, Random Forest, and SVM for UAV detection and classification. The framework compares radar signal data with the known UAV information and parameters for enhanced authentication.

3) The detection, classification, and authentication performances of the proposed frameworks are evaluated on the generated radar dataset. Detailed comparisons show that the proposed framework improves detection accuracy and achieves reliable classification and authentication.

II. Related Work

This section reviews the approaches and methodologies in UAV detection, emphasizing radar-based systems and machine-learning models for classification. A radar-based UAV detection method is proposed using the Empirical Mode Decomposition (EMD) algorithm to extract MD signals for identifying small UAVs [11]. The technique offers the advantage of isolating m-D features crucial for differentiating UAVs from other moving objects, decomposes signals into intrinsic mode functions (IMFs), and addresses mode-mixing challenges by analyzing the extrema distribution. The EMD algorithm distinguishes UAVs from birds or other objects based on their rotor blade signatures, making it highly effective even in noisy environments. In addition, the paper points that while the EMD algorithm effectively processes non-stationary signals, it also has limitations, such as susceptibility to noise and increased computational load, which may hinder its real-time application in practical UAV detection scenarios.

A. Radar Approaches, and Machine Learning Models UAV Classification

Ezuma et al. [9] presents a multistage system for detecting and classifying UAV controllers using radio frequency (RF) fingerprints in the 2.4 GHz band, even in environments with significant interference from Wi-Fi and Bluetooth devices. The system addresses the challenge of detecting UAV controllers in the presence of Wi-Fi and Bluetooth interference by first detecting RF signals using a Markov model-based Naïve Bayes algorithm, followed by interference detection and machine learning (ML) classification. The system extracts 15 statistical features from the UAV controller signals and achieves a classification accuracy of 98.13% using k-Nearest Neighbors (kNN) at 25 dB signal-to-noise ratio (SNR). Despite the effectiveness of the system, its limitation lies in distinguishing identical UAV controllers, such as pairs of DJI models, which slightly lowers accuracy due to signal similarity.

Meanwhile, a system proposes using Frequency Modulated Continuous Wave (FMCW) radar to detect and identify UAVs by analyzing their MD signatures [10]. It addresses the challenge of extracting MD signatures caused by the rapid rotation of UAV rotor blades, which introduces high-frequency variations in radar signals. The system proposes a new approach for studying MD signatures in UAVs and presents both simulation and experimental results to demonstrate the effectiveness of this method. The analysis showcases the ability of FMCW radar to capture fine-grained UAV motion details, allowing for more accurate UAV detection and identification. This work improves UAV detection in target-dense environments and shows the advantages of MD signature analysis for characterizing UAVs in real-time scenarios.

Similarly, a micro-motion model for detecting and identifying low-slow-small UAVs using radar systems is proposed [11]. The research focuses on the MD effects generated by the rotating blades of UAVs. It suggests a method to enhance detection performance by compensating for translational movement and employing an optimal demodulation operator for parameter estimation. The process improves the signal-to-noise ratio (SNR) and suppresses clutter, making it practical for detecting small UAVs even under challenging low-SNR conditions. The simulation and experimental results demonstrate the accuracy of the proposed technique in estimating MD parameters, which significantly aids in classifying UAVs based on their unique motion characteristics. This work is relevant for air defense systems identifying small, slow-flying UAVs based on radar signatures.

Besides, a study establishes a theoretical foundation linking the MD signatures and motion dynamics of small UAVs, focusing on analyzing the Doppler spectrum as a more efficient tool than joint time-frequency (JTF) images [12]. It explores how MD features, such as blade length, rotor rotation rate, and radial velocity, can be derived from the Doppler spectrum, aiding in detecting and classifying small UAVs. The study demonstrates the correlation between the spectral distribution and UAV physical specifications through simulation and measured data. Compared to JTF images, the Doppler spectrum provides significant computational and storage benefits while delivering accurate MD signatures. However, the study acknowledges challenges in detecting chopping frequencies and resolving smearing effects caused by multiple rotors, especially in practical scenarios with complex UAV dynamics. Future work will focus on refining algorithms to address these issues for more reliable UAV detection and classification.

In another development, a study explores the use of machine learning for drone classification based on radar signals [13]. It details the creation of datasets through simulation, considering radar specifications and SNR ranging from 0 to 20 dB. Each dataset, with 1000 spectrogram samples per class and smaller validation sets, was used to train a Convolutional Neural Network (CNN). The CNN architecture, comprising convolutional layers, SoftPlus activation, instance normalization, dropout, and linear layers, was adapted for different radar pulse repetition frequencies (PRFs). The performance of the model was evaluated using the macro-F1 score, with results showing the X-band 2 kHz PRF radar outperforming the W-band radar, especially at lower SNRs. The study revealed that while the X-band radar achieved an F1 score of 0.816±0.011, it struggled with false alarms, particularly with noise being confused with the DJI Matrice 300 RTK drone. The model exhibited robustness to varying blade pitch and SNR values, maintaining performance with different pitch values and showing reduced effectiveness at lower SNRs. Future work aims to investigate the impact of various wavelengths, explore more complex CNN architectures, and validate models with real-world data, addressing the current model's limitations and extending its applicability.

Furthermore, a novel lightweight architecture presents the development of an MD-based detection method called DIAT-RadSATNet, a deep CNN (DCNN) designed for the detection and classification of Small UAVs (SUAVs) using MD signatures [14]. The method addresses the growing need for efficient SUAV detection in both defense and civilian applications. The proposed architecture is lightweight, with 40 layers and only 0.45 million trainable parameters, achieving a high classification accuracy of 97.3%. The study indicates the radar system's ability to classify various SUAVs, such as quadcopters and bionic birds, through field experiments and ablation studies, demonstrating superior performance compared to existing models. The DIAT-RadSATNet's lightweight design allows for real-time implementation with reduced computational costs. However, the study acknowledges limitations, regarding the potential challenges in detecting SUAVs under complex environmental conditions and the need for further testing in diverse operational scenarios to validate the system's robustness and scalability.

Rojhani et al. [15] introduced a novel deterministic data augmentation method for UAV classification based on MD radar signatures. The technique generates synthetic training datasets using a physical radar backscattering model, reducing reliance on extensive measurement campaigns. Compared to conventional random signal processing augmentation, the deterministic approach produces datasets that maintain the physical integrity of features, resulting in better generalization and reducing classification bias. The study focuses on classifying UAVs based on their number of motors using CNN, achieving an accuracy of 78.68% and outperforming conventional augmentation methods, which resulted in 66.18%

accuracy with significant class bias. The results suggest that the deterministic augmenter provides more reliable and effective training datasets, for radar-based UAV classification, and can be extended to other scenarios, such as human recognition and medical imaging. The research indicates the potential for scaling this method to produce diverse datasets without costly and time-consuming measurement campaigns.

Further, a novel approach for UAV classification using radar digital twins is presented by generating full-wave electromagnetic simulations [16]. A Multiple-Input Multiple-Output (MIMO) radar system is simulated using CAD models of various UAVs to create radar datasets that include Range-Doppler and MD information. The datasets train a machine learning classifier, a one-versus-rest Support Vector Machine (SVM), for UAV detection and classification. The simulations allow for generating radar datasets without the need for expensive, time-consuming measurement campaigns. The study demonstrates high classification accuracy (minimum 97%) in multi-UAV scenarios, showing that the digital twin framework offers a flexible and cost-effective solution for UAV detection and classification in various operational conditions.

Moreover, a review of radar-based drone detection, tracking, and classification techniques focusing on real-world data from 25 drone trials using the Gamekeeper radar and over 55,000 trajectories and diverse drone types like the DJI Phantom 2 and DJI Inspire 2 is conducted [17]. The challenges established include differentiating drones from non-drones and managing varying SNRs. The performance metrics such as accuracy, F1 score, true positive confidence, false alarm rate, and classification time delay are discussed, with the false alarm rate remaining a significant hurdle. The study explores advancements in distributed and multi-static radar systems, quantum oscillators, advanced antennas, ML, and AI, emphasizing their role in improving automatic target classification (ATC). It suggests future directions, including leveraging cognitive radar systems, digital twins for rapid algorithm development, and integrating contextual and meta-level information to enhance performance. The study concludes that while radar systems have made significant progress, challenges remain, in complex environments, and suggests a multisensor approach for more robust detection and classification of drones.

Furthermore, a study proposes a fully convolutional network (FCN)-based approach for fast detection of UAVs using pulse Doppler radar. The traditional constant false alarm rate (CFAR) methods, effective for uniform backgrounds, struggle with low-small UAVs [18]. The proposed FCN operates on the entire range-Doppler map to enhance detection speed while maintaining high accuracy. The network leverages a bifurcated classification and regression architecture, reduces computational overhead, and integrates a post-processing mechanism for precise target location. The experimental results show the FCN-based method improves detection speed by up to 47 times compared to previous methods while ensuring high detection accuracy and reduced false alarms. Despite its achievements, it has difficulties detecting multiple UAVs in the same grid cell due to resolution constraints, with plans to address this via sampling in future research.

In another research, a study investigates the use of MATLAB simulations for analyzing MD signatures of rotating propeller blades and flapping wings using an S-band continuous-wave (CW) radar system [6]. The system demonstrates the effectiveness of the Short Time Fourier Transform (STFT) and Fast Fourier Transform (FFT) in distinguishing between the unique signatures of micro- UAVs and birds. It employed a 100 kHz sampling frequency and 700ms integration time, revealing significant Doppler shifts and frequency dispersion associated with different propeller blade lengths and flapping frequencies. The results show STFT's capability to provide detailed time-frequency analysis, contributing to improved detection and characterization of small UAVs and avian targets. This work supports the development of advanced radar systems for enhanced detection and tracking, aligning with the goals of optimizing UAV identification and authentication in the context of radar signal analysis.

B. *Research Gap*

Significant advancements in UAV detection, classification, and authentication are attained across various methods, as observed in literature and as depicted in Table I. Despite this strides, significant gaps remain, in datasets and radar-based detection approaches. The reviewed research often relies on proprietary datasets, limiting generalizability, which indicates the need for publicly available, standardized UAV/drone datasets to benchmark the systems. In addition, radar systems are adequate for general UAV detection but lack robust methods for identifying specific UAV types based on MD or RCS features. Further innovation is needed to improve radar detection capability and address environmental challenges in urban areas, such as noise and clutter. To address these gaps, our research aims to develop a novel raw dataset for UAV identification and authentication, leveraging unique features and employing three models, kNN, Random Forest, and SVM, to classify UAVs based on their MD signatures. This proposed approach will enhance the accuracy of radar-based systems and utilize MD signatures for identity-based detection and authentication of UAVs.

TABLE I. COMPARATIVE ANALYSIS OF RELATED WORKS

Study	*Methodology*	*Main Features*	*Accuracy/Performance*	*Limitations/Challenges*	*Future Work*
(Zhao & Su, 2020)	EMD algorithm for MD extraction	Isolation of MD features of UAVs	Effective in noisy environments, good UAV differentiation	Computational load affects real-time performance	Optimizing real-time application and noise handling
(Ezuma et al., 2020)	RF fingerprints for UAV controller detection	Detects UAV controllers in noisy RF environments	Classification accuracy of 98.13% using kNN at 25 dB SNR	Struggles with identical controllers, limited in low SNR	Sensor fusion for improved UAV detection

Study	***Methodology***	***Main Features***	***Accuracy/Performance***	***Limitations/Challenges***	***Future Work***
(Reddy & Peter, 2021)	FMCW radar and MD signatures	Analyzes MD signatures caused by rapid rotor blade rotation	Effective in capturing fine-grained UAV motion details; improve detection in dense environments	Challenges in extracting MD signatures and dealing with high-frequency variations	Improve techniques for better MD signature extraction and analysis
(Ji et al., 2021)	Micro-motion model and radar systems	Enhances detection performance for small UAVs; improved signal-to-noise ratio (SNR) and optimal demodulation	Accurate in estimating MD parameters; effective in low-SNR conditions	Detection challenges due to clutter and small UAV dynamics	Refine algorithms for better performance in cluttered environments
(Kang et al., 2021)	MD signatures and Doppler spectrum	Links MD signatures to UAV motion dynamics; efficient compared to joint time-frequency (JTF) images	Accurate with significant computational and storage benefits; good correlation with UAV specs	Detection challenges due to chopping frequencies and smearing effects from multiple rotors	Refine algorithms to address detection challenges with complex UAV dynamics
(Raval et al., 2021)	Machine learning with radar signals and CNNs	Creates datasets with different radar specifications; evaluates X-band vs. W-band radar performance	X-band radar achieved F1 score of 0.816±0.011; struggles with false alarms at lower SNRs	False alarms due to noise confusion; reduced effectiveness at lower SNRs	Investigate impact of different wavelengths and complex CNN architectures; validate with real-world data
(Kumawat et al., 2022)	MD-based detection with DIAT-RadSATNet	Lightweight DCNN architecture with 40 layers and 0.45 million parameters; high classification accuracy	Achieves 97.3% classification accuracy; real-time implementation with reduced computational costs	Challenges in detecting SUAVs under complex conditions; needs further testing in diverse scenarios	Validate system's robustness and scalability in various operational environments
(Rojhani et al., 2023)	Deterministic data augmentation for UAV classification using MD radar	Generates synthetic datasets using radar backscattering; focuses on UAVs classified by motor count with CNN	Achieved 78.68% accuracy; outperformed conventional augmentation methods (66.18%)	Class bias with conventional methods; potential for scaling to other domains like human recognition and medical imaging	Extend method to diverse scenarios and other applications such as human recognition and medical imaging
(Sayed et al., 2023)	Radar digital twins for UAV classification using electromagnetic simulations	Simulates MIMO radar with CAD models to generate datasets; uses SVM for classification	Achieves minimum 97% classification accuracy in multi-UAV scenarios	Cost-effective but requires validation in real operational conditions; limited to simulated scenarios	Validate system in real-world scenarios and diverse conditions
(Ahmad et al., 2024)	Radar-Based Detection and Tracking	Reviews radar systems and performance metrics; discusses advancements in radar technology.	Metrics discussed include accuracy, F1 score, and false alarm rate; specifics not provided.	False alarm rates and differentiation challenges; complex environments.	Multisensor approaches and cognitive radar for improved performance.
(Tian et al., 2024)	Fully Convolutional Network (FCN) for Fast Detection	Uses FCN for enhanced speed and accuracy in detecting UAVs; bifurcated architecture for classification.	47 times faster detection speed; high accuracy and reduced false alarms.	Difficulty in detecting multiple UAVs in the same grid cell.	Up-sampling techniques to address resolution constraints.
(Zulkarnain et al., 2024)	MATLAB Simulations of MD Signatures	Analyzes MD signatures using STFT and FFT to distinguish UAVs from birds.	Effective in distinguishing UAVs from birds; detailed time-frequency analysis.	Limited by radar system capabilities and integration time.	Advanced radar systems for improved detection and tracking.
Proposed Model	Micro-Doppler Signature and Doppler Spectrum	Uses Radar system for detection, kNN, Random Forest, and SVM for classification.	Achieves 100% accuracy with Random Forest.	kNN, and SVM are struggling in distinguishing some types of UAVs due to their similarities.	To integrate RID Policy in UAVs detection and authentication.

III. Simulation Setup

This research presents a novel approach to generating a raw dataset of UAVs, focusing on three distinct types: the DJI Matrice 600, DJI Matrice 300, and DJI Phantom 4. The dataset is designed to capture radar signals reflective of these UAVs' unique characteristics, facilitating a detailed analysis of their operational signatures. The radar system is configured to simulate detections of the UAVs at distances of up to 1 kilometer in both hovering and motion operations. This involves UAVs located 1 kilometer towards the radar and 1 kilometer away from it, with all the points between the intervals of 10 meters inclusive. The simulation considers various UAV operations, such as stationary hovering and different flying speeds, providing a robust dataset that reflects real-world operational conditions. The generated data, which encompasses detailed radar reflections and MD signatures unique to each UAV type, is used to train machine learning models utilizing kNN, Random Forest, and SVM algorithms. These models are employed to classify and detect UAVs based on their distinct radar signatures, enhancing the system's capability to differentiate between the DJI Matrice 600, DJI Matrice 300, and DJI Phantom 4 across various operational modes. This research contributes to advancing more effective and precise UAV detection and classification systems.

The flowchart in Fig. 1 illustrates the detection and classification processes. Radar sends continuous signals to detect UAVs and collects return signals for analysis. The data is processed through the three models. In kNN, the Euclidean distance between the test data and training samples is calculated, and the UAV is classified based on the majority class among the five (5) nearest neighbors. While, Random Forest uses feature selection and bootstrapped datasets to train multiple decision trees, and combine their votes to classify the UAV. As SVM involves feature selection, kernel function selection (linear, polynomial, or RBF), hyperplane construction, and margin maximization to separate classes, and classify UAV based on a one-vs-all strategy. Then, the model with the highest accuracy is chosen to make the final classification decision. This ensures a systematic approach to UAV detection and classification using machine learning, and demonstrates the complementary work by the three integrated models.

A. UAV Parameters

The three simulated UAVs have the following parameters:

1) DJI Matrice 600: It is set to have $N_r^{M600} = 6\, rotors$, blades with a length $L_b^{M600} = 0.5\, m$, a rotor speed $\omega^{M600} = 2200\, RPM = 36.7\, Hz$, a propeller distance $D_p^{M600} = 1.13\, m$, and $N_a^{M600} = 6\, arms$.

2) DJI Matrice 300: It is set to have $N_r^{M300} = 4\, rotors$, blades with a length $L_b^{M300} = 0.4\, m$, a rotor speed $\omega^{M300} = 2400\, RPM = 40.0\, Hz$, a propeller distance $D_p^{M300} = 0.885\, m$, and $N_a^{M300} = 4\, arms$.

3) DJI Phantom 4: It is set to have $N_r^{M600} = 4\, rotors$, blades with a length $L_b^{P4} = 0.3\, m$, a rotor speed $\omega^{P4} = 3500\, RPM = 58.3\, Hz$, a propeller distance $D_p^{P4} = 0.35\, m$, and $N_a^{P4} = 4\, arms$.

These parameters are used to simulate the MD signatures generated by the rotor blades. The rotor speed (in Hz) and blade length define the periodic motion, while the propeller distance and number of arms influence the radar reflections. This level of detail is essential for modeling radar signals that differentiate between UAV types based on their distinct physical characteristics. The factors are significant in generating unique MD patterns that facilitate the classification and identification of the UAVs.

B. Radar Parameters

The radar system is simulated to operate in this research at a carrier frequency, $f_c = 77\, GHz$. It features a maximum range (detectable range), $R = 1200\, m$ and a range of resolutions, $\Delta R = 1\, m$. The radar's bandwidth is calculated as the speed of light divided by twice the range resolution, $B = \frac{c}{2\Delta R} = 150\, MHz$. The sweep time, $T_s = 5.5\, seconds$, while the chirp slope is derived from the bandwidth and sweep time, $\Upsilon = \frac{B}{T_s} = 2.27 \times 10^6\, Hzs^{-1}$. The radar's maximum beat frequency and range beat frequency, $f_{beat,max}$ are set to handle the operational parameters effectively. The system supports MD processing for velocities, $V_{max} = 50\, ms^{-1}$, with the maximum Doppler frequency set to accommodate these speeds, $f_{doppler} = \frac{2V_{max}f_c}{c} = 25.67\, kHz$. The radar simulation encompasses, $N_p = 10\, pulses$ each consisting of $N_c = 60\, chirps$ and $N_s = 80\, samples\ per\ chirps$. The pulse repetition frequency (PRF) is determined based on these parameters where Np, Nc, and Ns stand for number of pulses, number of chirps, and number of samples respectively.

1) Transmitted chirp signal: The transmitted chirp signal models how the radar transmits a signal over time. This chirp signal is essential for determining the range and Doppler characteristics of UAVs. The selected UAVs in this research are DJI Matrice 600, DJI Matrice 300, and DJI Phantom 4. Hence, the chirp signal detects and measures their distance and movement by analyzing the returned signals as in Eq. (1),

$$S_r(n,t) = a_t rect\left(\frac{\hat{t} - t_d}{\tau}\right) e^{j[2\pi f_c t_d + \pi\Upsilon(\hat{t} - t_d)^2]} \tag{1}$$

where $S_r(n,t)$, is the transmitted baseband signal from the radar at the time $\hat{t}$ for the nth pulse and a_t is the amplitude of the return signal, often defined by the radar range equation, and it depends on the transmitted power, target radar cross-section (RCS), and range. While $rect\left(\frac{\hat{t}-t_d}{\tau}\right)$ is the rectangular window function that represents the radar pulse shape. The function limits the signal to the time interval τ, which is the pulse width. It centers on the delayed time, t_d where t_d is the round-trip time delay is related to the range R of the target by $t_d = \frac{2R}{c}$. Meanwhile, $e^{j[2\pi f_c t_d + \pi\Upsilon(\hat{t} - t_d)^2]}$ is the complex exponential that describes the frequency modulation (FM) of the chirp signal and f_c is the radar's carrier frequency (center frequency of the transmitted signal). In addition, γ is the chirp rate or chirp slope, representing the rate of frequency change in the transmitted chirp signal and $(\hat{t} - t_d)^2$ represents the quadratic phase term, where $\hat{t}$ is the time within a pulse and t_d is the delay due to the target's range.

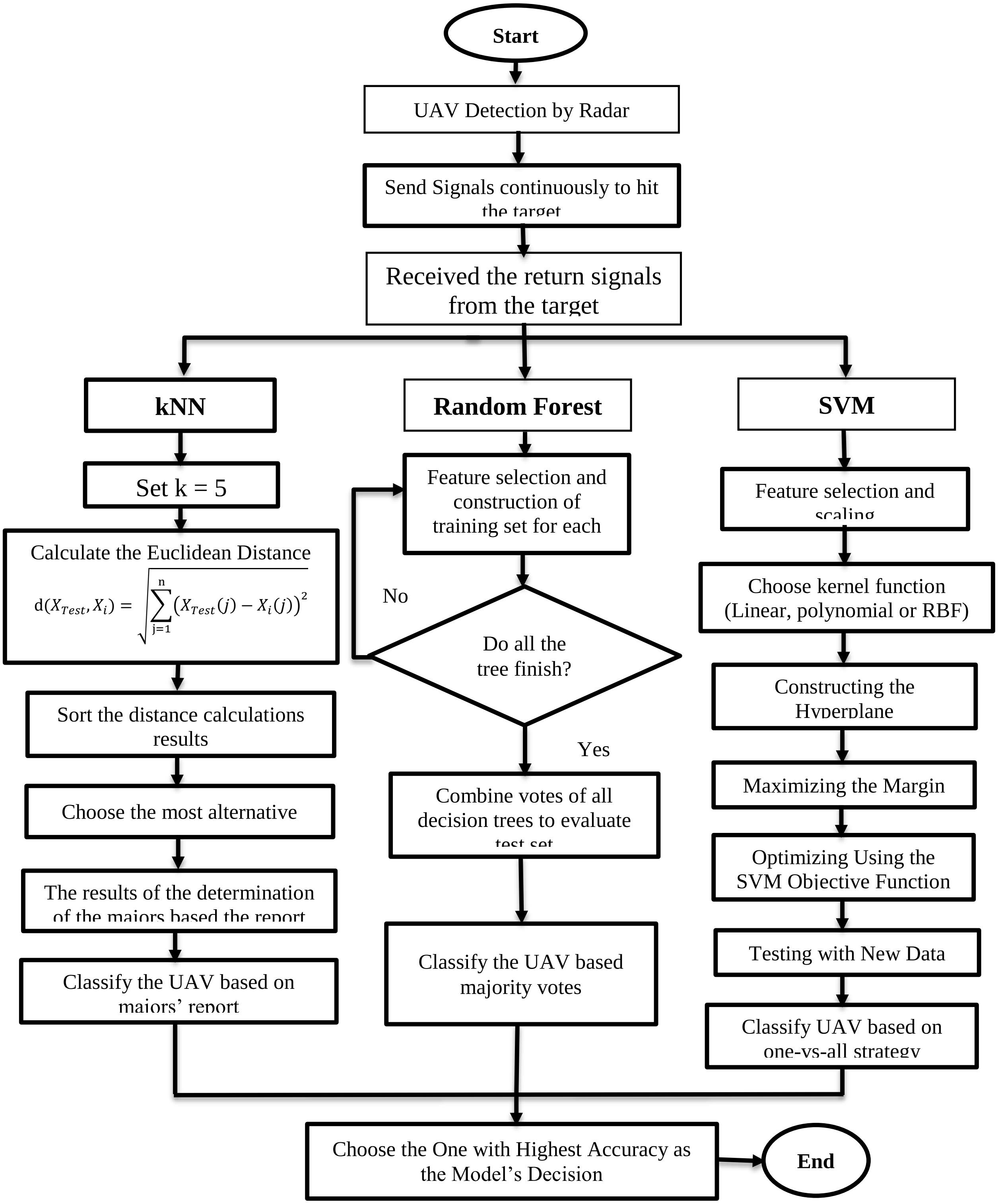

Fig. 1. Flowchart of the proposed model.

2) Received chirp signal: The received chirp signal $S_R(t)$ models the interaction between the radar and UAVs. The time delay τ =2r/c reflects the time it takes for the radar signal to travel to the UAV and back. This model is crucial for calculating the distance of the UAVs from the radar. Therefore, the received signal can be written as in Eq. (2),

$$S_{received}(n,t) = S_{UAV}(n,t) + S_{clutter}(n,t) + Noise(0,\sigma^2) \quad (2)$$

where $S_{UAV}(n,t)$ is the signal reflected by the target (UAV), $S_{clutter}(n,t)$ is the clutter signal, which is the sum of reflections from multiple clutter sources and $Noise(0,\sigma^2)$ is the additive noise in Gaussian distribution.

3) Dechirped intermediate frequency signal: The dechirping is the mixing (multiplying) of the received signal with a delayed version of the transmitted signal (reference chirp). This multiplication produces the Intermediate Frequency (IF) signal as described in Eq. (3), which contains the difference between the transmitted and received frequencies.

$$S_{IF}(n,t) = S_{received}(n,t) \times S_r^*(n,t) \tag{3}$$

$S_r^*(n,t)$ is the complex conjugate of the transmitted signal $S_{received}(n,t)$. When the received signal is mixed with the conjugate of the transmitted chirp, the high-frequency terms cancel out, leaving behind a low-frequency signal (beat signal) that encodes target information such as range and Doppler shifts. The resulting signal $S_{IF}(n,t)$ will have components related to the difference in time delay and Doppler shift between the transmitted and received signals. The UAV reflection of the IF signal is given by Eq. (4), where $f_{beat} = f_c(t_r - t_d)$ is the beat frequency proportional to the time delay, $(t_r - t_d)$, which relates to the range of the target. $\phi(t)$ is the phase component, which includes Doppler frequency information.

$$S_{IF,UAV}(n,t) = a_r rect\left(\frac{\hat{\mathrm{t}} - \mathrm{t_r}}{\tau}\right) e^{j[2\pi f_{beat} t + \phi(t)]} \tag{4}$$

The IF signal after dechirping contains beat frequency and phase modulation. The beat frequency is proportional to the range of the UAV (or other targets); the greater the range, the higher the beat frequency. Meanwhile, phase modulation is caused by Doppler shifts, which provide information about the relative velocity of the UAV.

4) Dechirped signal: The dechirped signal, $S_0(t, t_s)$ assists in analyzing the radar return signal by removing residual phase terms. This step is essential for accurately processing and analyzing the data collected from UAVs, ensuring that the range and Doppler measurements used for classification are precise. The dechirped signal would also include contributions from clutter and noise. Therefore, the IF signal after dechirping becomes Eq. (5), where, $S_{IF,UAV}(n,t)$ is the beat signal from the UAV, while $S_{IF,clutter}(n,t)$ represents the beat signals from clutter sources and $Noise(0,\sigma^2)$ is the noise (modeled as Gaussian noise).

$$\begin{aligned} S_{IF}(n,t) = S_{IF,UAV}(n,t) + S_{IF,clutter}(n,t) \\ + Noise(0,\sigma^2) \end{aligned} \tag{5}$$

5) MD effect: The MD effect is significant in detecting and identifying the UAVs' distinct features, such as rotor blades' motion. MD is a time-varying frequency shift caused by small periodic motions like the rotor blades of the UAV. It is modeled in Eq. (6) where, $v(t)$ is the instantaneous velocity of the rotating or moving part, λ is the wavelength of the radar signal, and $f_{mD}(t)$ represents the MD frequency shift.

$$f_{mD}(t) = \frac{2v(t)}{\lambda} \tag{6}$$

The overall received signal, including the MD effect, is represented in Eq. (7) where $2\pi f_c t_r$ is the bulk Doppler shift and the MD shift is $2\pi f_{mD}(t)t$.

$$\begin{aligned} &S_r(n,t) \\ &= a_r rect\left(\frac{\hat{\mathrm{t}} - \mathrm{t_r}}{\tau}\right) e^{j[2\pi f_c t_r + 2\pi f_{mD}(t)t + \pi \Upsilon(\hat{t} - t_r)^2]} \end{aligned} \tag{7}$$

6) Received Signal with MD and Noise: The total received radar signal, including the reflected signal from the UAV, clutter sources, MD effects, and noise, can be modeled in Eq. (8).

$$\begin{aligned} &S_{received}(n,t) \\ &= a_r rect\left(\frac{\hat{\mathrm{t}} - \mathrm{t_r}}{\tau}\right) e^{j[2\pi f_c t_r + 2\pi f_{mD}(t)t + \pi \Upsilon(\hat{t} - t_r)^2]} \\ &+ \sum_{i=1}^{N_c} a_{ci} rect\left(\frac{\hat{t} - t_{ci}}{\tau}\right) e^{j[2\pi f_c t_{ci} + 2\pi f_{mD}(t)t + \pi \Upsilon(\hat{t} - t_{ci})^2]} \\ &+ Noise(0,\sigma^2) \end{aligned} \tag{8}$$

C. File Format and Metadata

The data is stored in an Excel file and is organized into four sheets, each containing 8,120,601 samples of the three different UAVs (DJI Matrice 600, DJI Matrice 300, and DJI Phantom 4). The data is captured as the UAVs move within a 3D space ranging from 1 km away towards the radar to 1 km towards the radar. The movement is recorded at 10-meter intervals in each direction. Each sheet includes the following data for every sample: Raw RX Data, UAV Type, UAV Features, and Location. The captured information is utilized to train the machine learning models kNN, Random Forest, and SVM for classification purposes.

D. UAV Classification

The classification of UAVs is an approach for identifying UAV types and their operational modes based on the received radar information, specifically range-Doppler maps. The method leverages the kNN, Random Forest, and SVM algorithms, which classify a test sample by considering its proximity to the labeled training samples in features' space as described in equation (9). The dataset is represented as $X = \{\mathrm{x_1}, \mathrm{x_2}, \cdots, \mathrm{x_N}\}$, where, $\mathrm{x_i}$ represents the features of a sample, such as the range-Doppler map. Each $\mathrm{y_i} \in Y$, where Y contains UAV types or operational modes. yi ∈ {DJI Matrice 600, DJI Matrice 300, Phantom 4}

1) Data preparation and feature extraction: To train the classifiers for identifying UAV types and their operational states, the raw radar signal (range-Doppler maps) is first preprocessed. The range-Doppler map, which represents the response of the radar to a moving object in terms of range and velocity, is flattened into a one-dimensional vector. Mathematically, let the range-Doppler map for a UAV U and velocity V be denoted as $RD_{U,V}(r, f_D)$, where r represents range and f_D represents Doppler frequency. To simplify this for machine learning, each map $RD_{U,V}$ is reshaped into a feature vector $X_{u,v} \in \mathbb{R}^n$, where n is the total number of points in the range-Doppler map. Thus, the feature matrix X for all UAVs and states becomes Eq. (9):

$$X = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,V} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,V} \\ \vdots & \vdots & \ddots & \vdots \\ X_{U,1} & X_{U,2} & \cdots & X_{U,V} \end{bmatrix} \tag{9}$$

where U represents the number of UAV types and V represents the number of velocity states (including hovering). Each row in X corresponds to the real part of the radar signal response, ensuring compatibility with standard machine learning models as indicated in Eq. (10).

$$Y = \begin{bmatrix} UAV\ Type_1 & Operation_1 \\ UAV\ Type_2 & Operation_2 \\ \vdots & \vdots \\ UAV\ Type_N & Operation_N \end{bmatrix} \tag{10}$$

a) Dataset: The dataset consists of radar return signals from three different types of UAVs: DJI Matrice 600, DJI Matrice 300, and DJI Phantom 4. Each UAV is simulated, and its features are captured across a range of distances from the radar, spanning between [1000; 1000; 1000] meters (1km) towards the radar and [-100; -1000; -1000] meters (1km) away from the radar, with measurements taken in 10m intervals inclusive. The features extracted from the UAVs are the reflected radar signals from the UAVs that capture unique characteristics, structural design, movement patterns, and operational parameters such as rotor speed, body dimensions, and altitude. These features, derived from the signal's amplitude, phase shifts, and Doppler effects, provide distinctive signatures that can be used for identifying and classifying each UAV at various distances and orientations relative to the radar system. These reflected signals can be used to train machine-learning models to recognize the specific identity of each UAV, enabling robust identity-based authentication and detection. The dataset is extensive, capturing radar return signals from multiple locations within a specified range. Each UAV covering all locations within the range of [-1000; -1000; -1000] to [1000; 1000; 1000] at intervals of 10 meters, the total number of samples is calculated as the following.

Total samples per UAV:

$$\text{UAV} = 201 \times 201 \times 201 = 8,120,601$$

Therefore, the total dataset samples of the three UAVs (DJI Matrice 600, DJI Matrice 300, and DJI Phantom 4) is the total number of samples across the UAVs.

$$\begin{aligned}\text{Total Dataset Samples } &= 8,120,601 \times 3 \\ &= 24,361,803 \text{ samples}\end{aligned}$$

This results in a dataset containing 24,361,803 samples in total, providing unique radar profiles for each UAV at all specified distances. This comprehensive dataset enables efficient training of machine-learning models for UAV identification and classification based on their radar return signals.

The structure of the captured information is described as follows:

- Reflected Signal: This matrix captures the amplitude of the radar return signals reflected by the DJI Matrice 600 at [1000; 1000; 0]:

$$X = \begin{bmatrix} -1.15193589623129 & 2.79463633718335 & \cdots & 0.854456914633749 \\ -0.267289748658581 & -0.368824215433807 & \cdots & -0.671501576572502 \\ \vdots & \vdots & \ddots & \vdots \\ -0.382196398043339 & 0.0841435521978612 & \cdots & -1.14575173405667 \end{bmatrix}$$

- Drone Type: The UAV information captured is that of DJI Matrice 600.
- Drone Features: The details of the UAV captured include the number of rotors, rotor radius, rotor speed, and other relevant features [6 0.5 36.6666666666667 1.13 6].
- Location: Indicates the coordinates of the UAV towards the radar [1000; 1000; 0].

b) Feature extraction: The range-Doppler maps are generated from radar signals for each UAV, capturing significant features related to the movement and MD signatures of the drone. These maps encode essential information about the range and velocity of UAVs, making them a valuable feature set for classification tasks. The formula of Range-Doppler maps is defined in Eq. (11):

$$R_D(n,f) = FFT_t\{FFT_r\{S_r(n,t)\}\} \tag{11}$$

Therefore, the features extracted from the Range Doppler maps are Mean Range μ_r, Mean Doppler-Shift μ_d, Standard Deviation of Range σ_r, and Standard Deviation of Doppler Shift σ_d. These are described in Eq. (12), (13), (14), and (15) respectively. Others include Peak-to-Average-Ratio (PAR), Spectral Centroid (SC), Spectral Bandwidth (SB), Peak Amplitude (PA), Number of Peaks, Energy Ratio (ER), and Entropy. The PAR, SC, SB, PA, ER, and Entropy are represented in Eq. (16), (17), (18), (19), (20) and (21) respectively.

$$\mu_r = \frac{1}{N}\sum_{n=1}^{N} r(n) \tag{12}$$

$$\mu_d = \frac{1}{M}\sum_{f=1}^{M} d(f) \tag{13}$$

$$\sigma_r = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(r(n)-\mu_r)^2} \tag{14}$$

$$\sigma_d = \sqrt{\frac{1}{M-1}\sum_{f=1}^{M}(d(f)-\mu_d)^2} \tag{15}$$

$$(PAR) = \frac{max_d}{\mu_d} \tag{16}$$

$$SC = \frac{\sum_f f \times R_D(n,f)}{\sum_f R_D(n,f)} \tag{17}$$

$$BD = \sqrt{\frac{\sum_f (f - SC)^2 \times R_D(n,f)}{\sum_f R_D(n,f)}} \tag{18}$$

$$PA = max_{n,f} \times R_D(n,f) \tag{19}$$

The number of peaks counts the significant peaks in the range-Doppler map, which is related to the number of rotating blades or moving parts.

$$ER = \frac{\sum_{(n,f)\in Region} R_D(n,f)}{\sum_{n,f} R_D(n,f)} \tag{20}$$

ER is a ratio of energy in specific regions of the range-Doppler map to the total energy, which indicates specific features related to the UAVs.

$$Entropy = -\sum_{n,f} \frac{R_D(n,f)}{E} \, log\left(\frac{R_D(n,f)}{E}\right), \tag{21}$$

Where

$$E = \sum_{n,f} R_D(n,f)$$

Therefore,

$$Features\,Vector\,(F_i) = [\mu_r, \mu_d, \sigma_r, \sigma_d, PAR, SC, SB, PA, Number\ of\ Peaks, ER, Entropy\,]$$

The features vector provides a comprehensive representation of the UAV's radar signature that can ensure classification accuracy.

2) Training the classifiers: The kNN, Random Forest, and SVM classifiers are trained using the feature matrix X and the corresponding label matrix Y. The goal is to classify two outputs: the type of UAV and its operation. Let $y_{UAV\,Type}$ be the vector containing the UAV type labels, and $y_{Operation}$ be the vector containing the operational states (hovering or moving). The kNN classifier identifies the k nearest training points for each test point based on a chosen distance metric. In contrast, the Random Forest model uses an ensemble of decision trees to make predictions by averaging the outputs of multiple trees, while the SVM model finds the optimal hyperplane that maximizes the margin between classes for classification. Given a new test point $X_{Test} \in \mathbb{R}^n$, the classifier computes the distances to all training points $X_i \in \mathbb{R}^n\ in\ X$ as in Eq. (22).

$$\mathrm{d}(X_{Test}, X_i) = \sqrt{\sum_{j=1}^{n} \left(X_{Test}(j) - X_i(j)\right)^2} \tag{22}$$

The kNN, Random Forest, and SVM classifiers are each used to classify both UAV type and operational state. The kNN classifier identifies the k nearest points and uses majority voting to assign the test point X_{Test} to a class for both the UAV type and the operation. While Random Forest aggregates predictions from decision trees, and SVM identifies the optimal hyperplane to separate classes. In this case, two separate classifiers are trained: one for UAV-type prediction and one for operational state prediction.

3) Classification: The kNN, Random Forest, SVM models are trained to classify new radar signal data from unknown UAVs. For each radar signal, represented by its corresponding range-Doppler map X_{Test}, the models predicts both the UAV type and its operation. The UAV type classifier, $f_{UAV\,Type}$, assigns a predicted class label based on the features of the test data:

$$\hat{y}_{\mathrm{UAV\,Type}} = \mathrm{f}_{\mathrm{UAV\,Type}}(\mathrm{X}_{\mathrm{Test}}) \tag{23}$$

Similarly, the operation classifier, $f_{Operation}$, predicts the UAV's operational state by analyzing the same test signal.

$$\hat{y}_{Operation} = f_{Operation}(X_{Test}) \tag{24}$$

Both classifiers work in tandem to identify the UAV type and its operational state from the radar signal data, making predictions based on the nearest neighbors in the training set.

E. *Visualization of the Signals*

The visualization of radar signals from various UAVs is critical for understanding their operational characteristics and enhancing classification tasks. The research used the generated raw data to visualize the UAVs' extracted features through maps. These maps include time/frequency spectrograms, mean spectrograms, and range-Doppler maps of the captured signals to facilitate detailed analysis of UAV's behaviors under different conditions.

1) Time/Frequency-Spectrograms: The time/frequency spectrograms provide a dynamic view of how the frequency content of the radar signals varies over time. The spectrograms get frequency on the vertical axis and time on the horizontal axis to demonstrate how the UAV's motion influences the received radar signals. Fig. 2 depicts rapid changes in frequency, indicating a UAV accelerating or maneuvering, while stable frequency patterns suggest hovering or cruising at a constant speed. This visualization is particularly useful for identifying unique operational signatures associated with different UAV types.

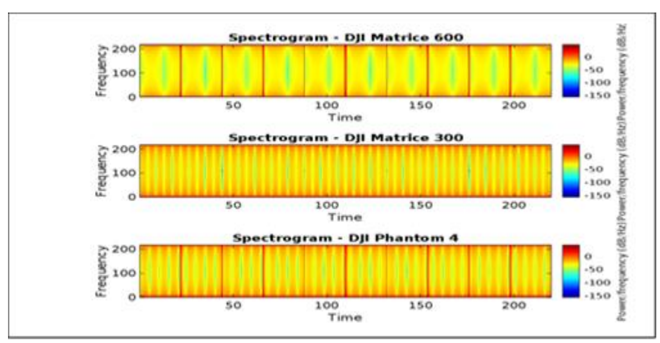

Fig. 2. UAV spectrograms.

2) Time/Frequency-mean spectrograms: The mean spectrograms is generated by averaging on multiple time/frequency spectrograms to emphasize the consistent features inherent to each UAV type. The smoothing out the variability in individual recordings, mean spectrograms highlight the dominant frequencies and patterns associated with specific UAVs as indicated in Fig. 3. This helps in distinguishing between UAVs, as each type tends to exhibit distinct frequency profiles that can be utilized for classification.

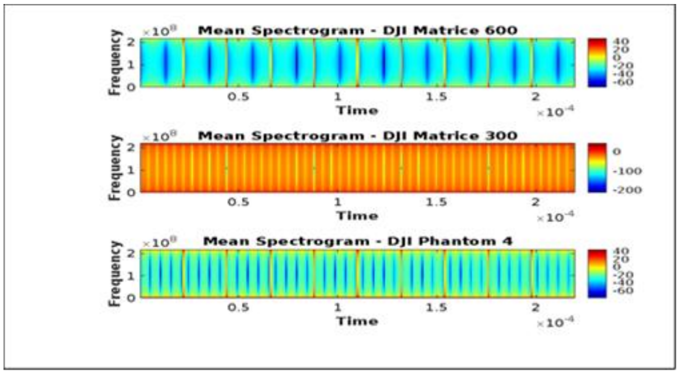

Fig. 3. UAV mean spectrograms

3) Doppler frequency/Range-Range-Doppler map: The Range-Doppler maps are pivotal in integrating both range and Doppler information into a single representation as indicated in Fig. 4. These maps reveal the detected UAVs' characteristics in a comprehensive manner. The intensity of the colors within the maps indicates the strength of the received radar signals, highlighting features specific to different UAV types. The variations in intensity help to differentiate between larger UAVs, which may have a stronger radar return, and smaller ones, which produce weaker signals.

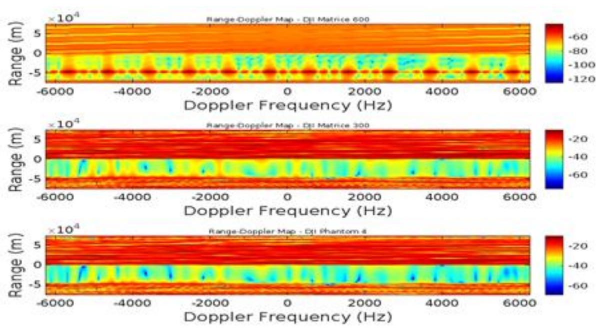

Fig. 4. UAV Range-Doppler Map

4) Doppler frequency/Range-Mean Range-Doppler maps: The mean range-Doppler maps are generated by averaging the range-Doppler data over multiple samples. This process reduces noise and highlights the typical signatures of each UAV type as described in Fig. 5. The mean range-Doppler maps assist in the classification process, making it easier to identify the unique characteristics associated with each UAV.

5) Doppler intensity plots: The Doppler intensity plots focus on specific points within the Doppler domain, illustrating the intensity of the received signals at various frequencies as presented in Fig. 6. These plots are beneficial for examining how signal intensity varies with Doppler frequency, offering insights into the operational states of the UAVs. The frequencies exhibit higher intensity levels during specific operations, such as takeoff or landing, enabling observers to infer the UAV's activity at a given time.

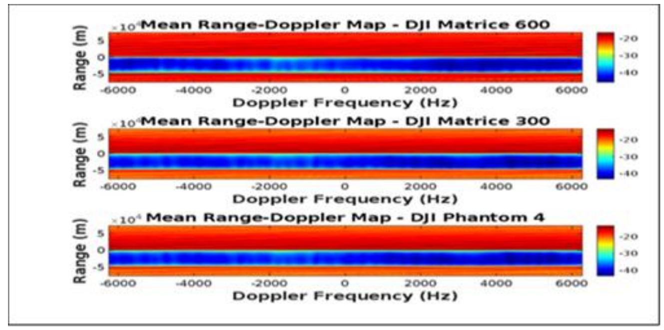

Fig. 5. UAV mean range-doppler map.

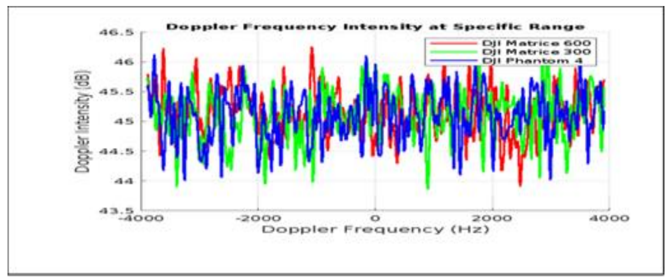

Fig. 6. UAV doppler frequency intensity.

IV. Evaluation and Testing

The captured radar signals information is deployed to kNN, Random Forest, and SVM to enable real-time classification of unknown UAVs based on their range-Doppler signatures. The relevant features are extracted from the radar signal and input into the classifiers to predict both the UAV type and its operational state (e.g., hovering or moving). The performances of the models are evaluated by comparing the predictions with the known ground truth. The performance metrics include classification accuracy, the F1 score, true positive confidence, and the false alarm rate. Additionally, the classification time delay is assessed to determine how fast the system can make predictions to ensure the model's viability for real-time UAV detection and authentication. These metrics provide an inclusive assessment of the classifier's effectiveness in accurately identifying UAV types and operational states from radar data.

1) Accuracy: This measures the proportion of correct predictions out of the total predictions made by the classifier.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{25}$$

where TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative.

2) F1 Score: It provides a balance between precision and recall, especially useful for imbalanced classes. It is the harmonic mean of precision and recall.

$$F1\ Score = 2 \times \frac{Precision\ \times\ Recall}{Precission +\ Recall} \tag{26}$$

Where

$$Precision = \frac{TP}{TP+FP}, \text{ and } Recall = \frac{TP}{TP+FN}$$

3) True positive confidence: This reveals the confidence level of the classifier in its correct predictions, expressed in a percentage form. It is the average confidence score assigned to true positive predictions.

$$TPC = \frac{\Sigma_{1=1}^{n} Confidence\ (TP_i)}{n} \tag{27}$$

where TP_i is the confidence of each true positive prediction and n is the number of classes.

4) False Alarm Rate (FAR): This indicates the number of times the classifier incorrectly predicts the presence of a UAV when there is none (false positive rate).

$$FAR = \frac{FP}{FP+TN} \tag{28}$$

5) Classification time delay: It measures the time taken for the classifier to process the radar signal and make a prediction. This is critical for real-time systems and can be represented as:

$$CTD = t_{end} - t_{start} \tag{29}$$

Where CTD is the classification delay time.

V. Result and Discussion

The results of classification performance of the three models (kNN, Random Forest, and SVM) have been evaluated across three UAV classes (DJI Matrice 600, DJI Matrice 300, and DJI Phantom 4). The results, as presented in confusion matrices shown Fig. 7, Fig. 8, and Fig. 9, and summarized in Table II, Table III, and Table IV, provide overview of how each model performs. The performances are in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), offering insights into their strengths and weaknesses.

	1	2	3	Percentage %	
1	36	4	4	89.40%	10.60%
2	4	18	22	62.90%	37.10%
3	2	19	23	62.90%	37.10%

Fig. 7. kNN's classification confusion matrix.

TABLE II. kNN's Classification Summary

Class	*TP*	*TN*	*FP*	*FN*
1 (DJI Matrice 600)	36	82	6	8
2 (DJI Matrice 300)	18	65	23	26
3 (DJI Phantom 4)	23	60	26	23
Total	**77**	**207**	**55**	**57**

The kNN exhibits varying levels of performance in the classification of UAV types. Class 1 (DJI Matrice 600): The classifier performs well and achieved 36 (TPs) with minimal FP (6) and FN (8). It shows the highest accuracy (89.4%) in this class, indicating that it can effectively distinguish the DJI Matrice 600 from the other UAVs. However, the classifier struggles with Class 2 (DJI Matrice 300), where it only correctly identifies 18 samples as Matrice 300, while misclassifying 23 samples from other classes as Matrice 300. In addition, it misses 26 actual Matrice 300 samples, leading to a moderate performance in the class. While, in Class 3 (DJI Phantom 4), kNN performs moderately well but faces challenges in balancing FPs and FNs, correctly classifying 23 samples as Phantom 4, while misclassifying 26 samples from other classes and failing to classify 23 actual Phantom 4 samples.

	1	2	3	Perc. %
1	44			100%
2		44		100%
3			44	100%

Fig. 8. Random forest's classification confusion matrice.

TABLE III. Random Forest's Classification Summary

Class	*TP*	*TN*	*FP*	*FN*
1 (DJI Matrice 600)	44	88	0	0
2 (DJI Matrice 300)	44	88	0	0
3 (DJI Phantom 4)	44	88	0	0
Total	**132**	**264**	**0**	**0**

In contrast, the Random Forest demonstrates outstanding performance in classifying all the UAV classes, and achieved 100% classification with no FPs or FNs, as indicated in Table III. Each class (DJI Matrice 600, DJI Matrice 300, and DJI Phantom 4) samples are correctly classified, and no misclassifications occur. It recorded 132 (TPs) and 264 (TNs) across all classes, and achieved an accuracy of 100%, showcasing its robustness and ability to effectively separate UAV classes. This perfect performance shows the utility of Random Forest for UAV detection and classification tasks, indicating that it can reliably distinguish between different UAV types without ambiguity.

Meanwhile, the SVM model performs well, with strong results across all three classes. Class 1 (DJI Matrice 600), the SVM achieves perfect classification, with 100% precision and 100% recall, correctly identifying all instances of this class. This suggests that the SVM model excels at detecting the DJI Matrice 600 UAV. While, in Class 2 (DJI Matrice 300), the model achieves a precision of 79.1% and a recall of 86.4%, with a resulting F1-score of 0.826. While some FPs are present, the model correctly identifies the majority of DJI Matrice 300 instances, but occasional confusion with other UAV types lowers its performance slightly. Also, in Class 3 (DJI Phantom 4), the SVM model achieves 85% precision and 77.3% recall, with an F1-score of 0.81. While the model correctly identifies most Phantom 4 samples, some instances are misclassified as other UAV types.

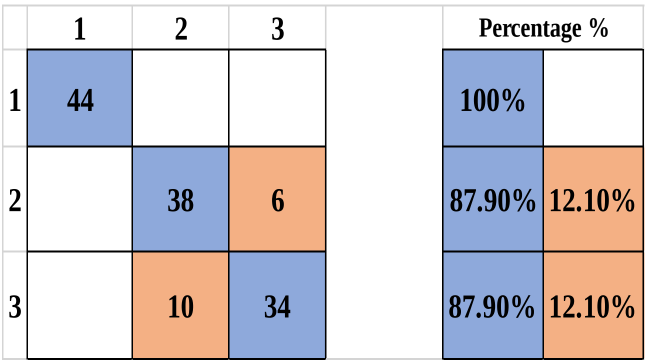

Fig. 9. SVM's classification confusion matrice.

TABLE IV. SVM'S CLASSIFICATION SUMMARY

Class	*TP*	*TN*	*FP*	*FN*
1 (DJI Matrice 600)	44	88	0	0
2 (DJI Matrice 300)	38	78	10	6
3 (DJI Phantom 4)	34	82	6	10
Total	**114**	**248**	**16**	**16**

TABLE V. SUMMARY OF PERFORMANCE OF THE THREE MODELS

Class	*Accuracy*	*F1 Score*	*TPC*	*FAR*
kNN	71.73%	58.14%	58%	0.21
Random Forest	100%	100%	100%	0.00
SVM	93.27%	88%	87%	0.06

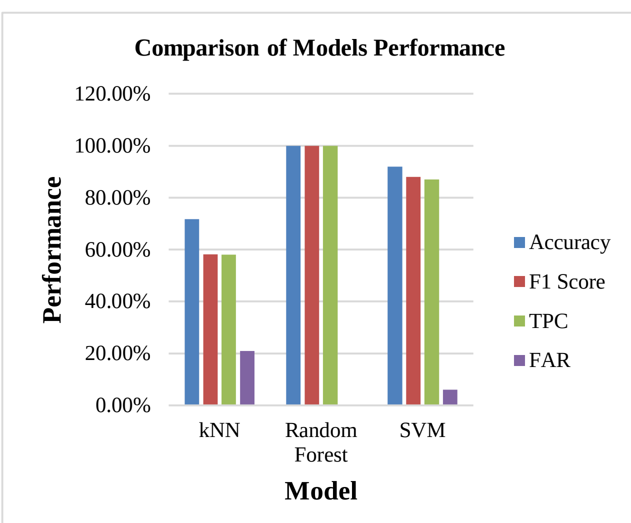

Fig.10. Models performances.

The Random Forest emerged as the best-performing model due to its perfect classification accuracy (100%) and zero false alarms as shown in Fig. 10 and Table V. This makes it well-suited for real-time UAV monitoring, where minimizing errors is paramount. Although kNN and SVM achieved high accuracy for some UAV types, their issues with misclassifying between DJI Matrice 300 and Phantom 4 suggest that further tuning or additional feature engineering is needed to improve their performance in distinguishing these specific UAV types.

VI. CONCLUSION AND FUTURE DIRECTION

This research presents significant strides in the detection and authentication of UAVs through the creation of a unique radar dataset comprising three distinct UAV models (DJI Matrice 600, DJI Matrice 300, and Phantom 4). The research has laid the groundwork for enhanced UAV detection and classification. The utilization of MD radar signals allows for detailed analysis of UAV characteristics, facilitating accurate identification and robust authentication processes. Among the three machine learning models tested, Random Forest demonstrated exceptional performance, achieving 100% classification accuracy with zero false alarms, making it highly suitable for real-time UAV monitoring where precision is critical. While kNN and SVM models also showed strong results, they encountered misclassification issues attributed to the similarities in the radar signatures of the DJI Matrice 300 and DJI Phantom 4 UAVs. These UAVs share the same number of rotors and propellers, as well as other design features. Their structural similarities result in overlapping micro-Doppler effects and radar reflections, making it difficult for the models to distinguish between the two UAV classes, suggesting a need for further refinement.

However, future work will focus on developing a system that leverages the Remote ID (RID) policy, and the radar datasets generated in this study to improve the detection, identification, and authentication of UAVs. The system will utilize the kNN, Random Forest, and SVM models, with particular attention to improving the performance of kNN and SVM to reduce misclassifications and enhance accuracy. These enhancements, combined with the broader application of RID data, will enable a more robust scalable solution that will detect and identify unknown UAVs and ensure monitoring and security in various operational environments.

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