Advancements in UAV Detection and Classification: Fusion of Mechanical Control and Sensor Data

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ABSTRACT

This research investigates the classification of unmanned aerial vehicles (UAVs) using micro-Doppler signatures, a crucial technique for discerning between different types of UAVs. Through the utilization of a full-wave electromagnetic CAD tool, we explore the influence of control systems on the range–Doppler signatures of various UAV configurations, including quadcopters, hexacopters, and helicopters. Our approach integrates a mechanical control-based machine learning (ML) algorithm, with convolutional neural networks (CNNs) demonstrating robust performance, achieving classification accuracies exceeding 90%. Additionally, we introduce a novel methodology for simulating radar datasets using CAD tools, enabling the generation of diverse datasets tailored to different drone types and radar parameters. Leveraging a simulated 77 GHz frequency-modulated continuous wave (FMCW) radar, our classification model attains an accuracy of over 97%. We establish a theoretical framework linking micro-Doppler signatures with UAV motion dynamics, providing insights into spectral distribution. Experimental analysis, combining simulations and measured data, underscores the potential for effective detection and classification. Furthermore, we propose a ground-based surveillance radar system for drone detection, surpassing existing methods in both accuracy and computational efficiency. Validation through field experiments with a commercial portable radar underscores the viability and effectiveness of our approach. Overall, this study contributes to advancing UAV classification techniques and enhancing drone detection capabilities in practical scenarios.

Keyword: *UAV classification, micro-Doppler signatures, range–Doppler images, machine learning, radar simulations, Doppler spectrum, ground-based surveillance radar, FMCW radar, CNN.*

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1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have transformed numerous sectors, from logistics to surveillance, owing to their versatility and accessibility. However, alongside their benefits, the proliferation of UAVs has introduced new challenges, including concerns regarding security, safety, and privacy. As UAVs become increasingly ubiquitous, the need for robust detection and classification methods becomes paramount to safeguarding critical infrastructure and public spaces.

Radar systems have emerged as a primary technology for UAV detection due to their ability to operate in diverse weather conditions and sense wide areas rapidly. Nevertheless, conventional radar systems face limitations in effectively detecting small UAVs, particularly those equipped with rotating blades, which generate micro-Doppler (MD) effects. Despite the promise of MD signatures for detection and classification, existing techniques encounter computational hurdles and require sophisticated signal processing methods.

A plethora of research endeavors has been dedicated to addressing the UAV detection and classification challenge. Some studies have explored time-frequency analysis techniques, utilizing Joint Time Frequency (JTF) images or Doppler spectra, while others have delved into the integration of mechanical control data with sensor data. Yet, there remains a gap in achieving accurate and efficient detection, especially in real-time scenarios and with ground-based surveillance radar systems.

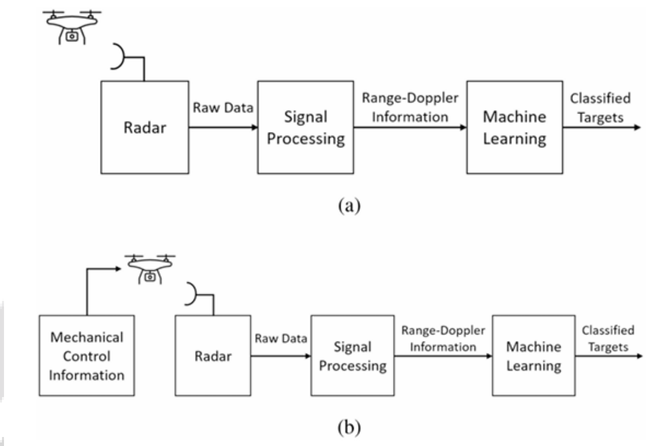

Fig -1: (a) Traditional method. (b) Proposed MCML method.

In response to this challenge, this research paper proposes a novel approach to enhance UAV detection and classification by synergizing mechanical control data with sensor data. Building upon the foundation laid by previous studies, our aim is to bridge the existing gaps and provide a robust solution for UAV detection and classification across diverse operational environments.

Central to our approach is the development of a comprehensive theoretical framework that establishes the intricate relationship between MD signatures and the physical specifications of UAVs, with a focus on Doppler spectrum analysis. We introduce two novel MD features derived directly from Doppler processing results, namely the number of P-crossings and local correlation of amplitude peaks, which capture both global and local MD information, respectively.

To validate the efficacy of our proposed method, extensive experimental analyses are conducted using real measurement data obtained from ground-based surveillance radar systems. These experiments serve to demonstrate the effectiveness and efficiency of our approach in detecting and classifying UAVs, even in challenging scenarios characterized by limited dwell time and complex environmental conditions.

The article presents a multifaceted approach to addressing challenges in drone detection using radar systems. Firstly, it focuses on generating radar datasets without constraints by leveraging full-wave EM CAD tools. Secondly, it employs machine learning (ML) algorithms to analyze the generated datasets, enhancing the understanding of drone signatures in radar data. Thirdly, the research delves into the impact of mechanical control information of drones on Radar Doppler (RD) signatures and ML classifier accuracy. To address this, a novel mechanical control-based ML (MCML) algorithm is proposed, aiming to preserve ML accuracy by incorporating mechanical control data. Figure 1(a) illustrates the conventional approach, while Figure 1(b) showcases the proposed MCML method. Lastly, the article conducts an extensive investigation and comparison of different classifiers using radar drone datasets that consider mechanical control information, providing insights into classifier performance under varying conditions.

2.RELATED WORK

In their paper titled "Machine Learning for UAV Classification Employing Mechanical Control Information" [1], Ahmed N. Sayed, Omar M. Ramahi, and Georges Shaker from the University of Waterloo, Canada, address the urgent need for robust detection and classification methods for drones, particularly in light of recent incidents involving drone misuse in terrorist attacks and airport disruptions. They emphasize the importance of radar systems in drone detection due to their ability to operate in diverse conditions and track multiple drones simultaneously. The authors present detailed mathematical models for quadcopter and hexacopter drones, elucidating the equations governing their flight dynamics and emphasizing the role of rotor angular velocities in maneuvering and stability. They discuss simulation setups using electromagnetic simulation software to generate radar datasets, facilitating the analysis of mechanical control effects on radar signatures. Overall, their research aims to enhance the accuracy of drone classification algorithms by incorporating mechanical control information, thereby improving the effectiveness of UAV detection systems.

In their paper presented at the 2022 ICCSI, Wang, Wei, Li, and Xin from the Beijing Institute of Mechanical Equipment, China, address the crucial domain of small face detection within UAV command and control systems [2]. They highlight the lack of specific research on small face detection despite extensive work on general deep neural network object detection algorithms. Recognizing the importance of efficient detection methods for crowd monitoring and decision-making in UAV operations, the authors propose research ideas and optimization schemes focused on data and feature enhancement to improve small face detection accuracy. Their literature survey covers traditional face detection algorithms and the evolution towards neural network-based approaches, emphasizing challenges such as feature extraction and multi-scale feature fusion. They introduce the SCRFD algorithm as a case study, illustrating strategies like sample reallocation and computation redistribution to optimize small face detection performance. Through their research, they aim to contribute to advancements in small face detection technology, particularly within UAV systems, to enhance overall system efficiency and decision-making capabilities.

Afridi, Awan, and Iqbal from the National University of Sciences and Technology, Pakistan, present AWG-Detector, a machine learning tool for accurately detecting anomalies due to wind gusts (AWG) in the adaptive altitude control unit of an Aerosonde Unmanned Aerial Vehicle (UAV) [3]. They emphasize the critical need for such a tool to prevent costly adaptation failures in UAVs when exposed to unpredictable disturbances like wind gusts. The authors highlight the importance of an intelligent and adaptive control system for UAVs operating in uncertain environments and discuss the failures of traditional controllers under violent weather conditions. Their adaptive altitude control unit integrates a hybrid neuro-fuzzy-based pitch controller and a PI-based roll controller, but simulation results reveal shortcomings in quick adaptation to wind gusts. To address this, they propose the AWG-Detector, employing machine learning techniques for early anomaly detection. The development process involves dataset creation through extensive wind gust simulations, resulting in over 99% accuracy in anomaly detection. Their comparative study of classification algorithms identifies J48 decision tree as the most effective, achieving high accuracy with minimal false alarms and false normals. The paper concludes with plans to enhance the tool's capabilities and explore sensor fault detection integration.

[4] Niu, Run, Yi Qu, and Zhe Wang propose a method for UAV image detection using deep learning technology, addressing the growing concern over the improper use of UAVs and their impact on public safety. Their approach, detailed in "UAV Detection Based on Improved YOLOv4 Object Detection Model," involves enhancing the YOLOv4 object detection model with lightweight processing for faster detection and integrating the Coordinate Attention (CA) mechanism to improve detection accuracy. Experimental results demonstrate that their model, CA-YOLOv4-L, achieves an average accuracy of 94.63% on UAV images with a detection speed of 39.66FPS and reduces parameters by 34.8% compared to the original model. This research contributes to filling the gap in UAV detection technology, offering a promising solution with practical implications for urban surveillance and public safety (Niu, Qu, & Wang, 2021).

Vishnu Balachandran and Sarath S. from Amrita Vishwa Vidyapeetham, Amritapuri, India, propose a pioneering method for Unmanned Aerial Vehicle (UAV) detection utilizing Pix2Pix Generative Adversarial Networks (GANs) [5]. With the surge in UAV usage for illicit activities, traditional countermeasures prove inadequate against the evolving threat landscape. Recognizing the limitations of existing technologies such as radar and acoustic sensors, the authors advocate for optical sensor-based detection augmented by Pix2Pix GANs. This novel approach marks the first application of Pix2Pix GANs in UAV detection, showcasing promising results on the Drone vs. Bird dataset. Achieving a Precision of 0.93, Recall of 0.94, and F1-score of 0.934 for an IoU threshold of 0.5, the proposed method demonstrates efficacy even in challenging weather conditions. The study not only underscores the potential of Pix2Pix GANs in enhancing UAV detection capabilities but also suggests avenues for future research, including dynamic base image selection to further enhance system efficiency.

Ahmed N. Sayed and Michael M. Y. R. Riad from the University of Waterloo present a methodology for UAV classification employing machine learning and full-wave electromagnetic simulations at the 2022 International Telecommunications Conference (ITC-Egypt) [6]. Recognizing the need for accurate UAV classification amidst increasing concerns over security threats posed by drones, the authors propose a novel approach leveraging micro-doppler signatures and radar simulations. Traditional methods of generating datasets for radar drones' measurements are often constrained by factors such as available drones, radar parameters, and environmental conditions. To overcome these limitations, the authors introduce a simulation method using full-wave electromagnetic CAD tools to generate diverse datasets comprising various drone types, sizes, materials, and flight parameters. By simulating radar responses for five different types of drones, including fixed-wing, helicopter, and quadcopter models, the authors create a comprehensive dataset for training machine learning algorithms. Employing a convolutional neural network (CNN) algorithm, the authors achieve classification accuracies exceeding 97%. This innovative methodology enables researchers to simulate and create diverse datasets of drones without constraints, paving the way for improved classification accuracy across different scenarios.

In [7], Gupta et al. present a novel multiclass-target classification method for mmWave frequency modulated continuous wave (FMCW) radar, operating in the frequency range of 77-81 GHz. By utilizing custom range-angle heatmaps and machine learning tools, they achieve high accuracy in classifying objects such as humans, cars, and unmanned aerial vehicles (UAVs) from radar data obtained in real-world scenarios. Their technique involves increasing the radar's elevation field of view (FoV) by orienting the antennas vertically and improving azimuth FoV by mechanical rotation. The system utilizes YOLO v3 for real-time object detection, with training data generated from radar measurements. The method demonstrates robustness in various lighting conditions and achieves accuracies of 97.6% for UAVs, 99.6% for humans, and 98.1% for cars. The proposed radar classification technique holds significant potential for applications in autonomous systems, including traffic monitoring, surveillance, and control systems for both ground and aerial vehicles.

The analysis of micro-Doppler signatures of small UAVs based on the Doppler spectrum is a crucial area of research, offering insights into target detection and classification. While previous studies have primarily focused on joint time-frequency (JTF) images, recent investigations have highlighted the utility of Doppler spectrum analysis for understanding micro-Doppler effects. By establishing a theoretical foundation connecting micro-Doppler signatures with the motion dynamics of small UAVs, researchers have successfully analyzed spectral distribution using simulations and measured data. Experimental analysis using various types of small UAVs further validates the effectiveness of Doppler spectrum analysis for detecting and classifying these aircraft. This approach offers advantages over JTF images in terms of simplicity and computational efficiency, paving the way for enhanced detection techniques. However, challenges remain in accurately extracting and utilizing micro-Doppler features for classification, particularly regarding the automatic estimation of chopping frequency and addressing smearing effects caused by multiple rotors. Future research aims to develop algorithms for more effective detection and classification of small UAVs based on micro-Doppler signatures [8].

In their study on UAV detection systems, the researchers propose an innovative approach utilizing an X-band ground-based surveillance FMCW Doppler radar [9]. This novel system directly extracts two key features from Doppler processing results without relying on traditional time-frequency analysis techniques. These features, namely the number of P-crossing and the local correlation of m-DS amplitude peaks, offer a unique perspective on capturing both global and local micro-Doppler signature information. By applying these features to a binary-category classifier, the system achieves enhanced detection accuracy and computational efficiency compared to existing methods. The experimental results highlight the effectiveness of this approach, signaling potential advancements in UAV detection technology.

Flórez et al. provide a comprehensive review of techniques for detecting UAVs and UASs across audio, radiofrequency, and video domains, catering to various application scenarios from agriculture to security [10]. They delve into sound detection methods, including correlation techniques such as Pearson, Kendall, and Spearman, along with Linear Predictive Coding (LPC) and K-nearest neighbors algorithm. The authors also explore video detection methods, highlighting object movement-based approaches coupled with machine learning, such as SSD, Faster R-CNN, and YOLO, for effective detection and classification. The study evaluates the strengths and limitations of each method, underscoring the need for integrated systems to address diverse detection challenges efficiently. Additionally, they present a comparative analysis of different detection technologies, paving the way for future research to develop cost-effective multimodal systems tailored to specific deployment environments.

In their Correspondence, Sun et al. propose an Iterative Adaptive Approach (IAA) to enhance the Doppler resolution of ground-based surveillance radar for drone detection, addressing the challenge posed by limited dwell time. By iteratively adapting the algorithm based on weighted least squares, IAA achieves super-resolution with only a few or even one temporal snapshot. Simulation results demonstrate the superior performance of IAA over conventional Fast Fourier Transform (FFT) in Doppler estimation, even under noisy conditions and for non-stationary Doppler signals. Experimental validations conducted with a commercial portable ground-based surveillance radar confirm the efficacy of IAA in improving Doppler resolution, enabling clear discrimination of micro-Doppler signatures of drones. Furthermore, IAA enhances the detectability of slow-moving targets and ground clutter, thereby improving overall radar detection performance. Comparative analyses also reveal that IAA outperforms FFT in automatic drone classification, showcasing its robust and superior performance. This work provides a promising technique to replace FFT for Doppler processing in practical radar systems [11].

3.PROPOSED METHODOLOGY

3.1 Machine Learning for UAV Classification Employing Mechanical Control Information

The mathematical models for quadcopter and hexacopter drones describe their equations of motion in various flight conditions [1].

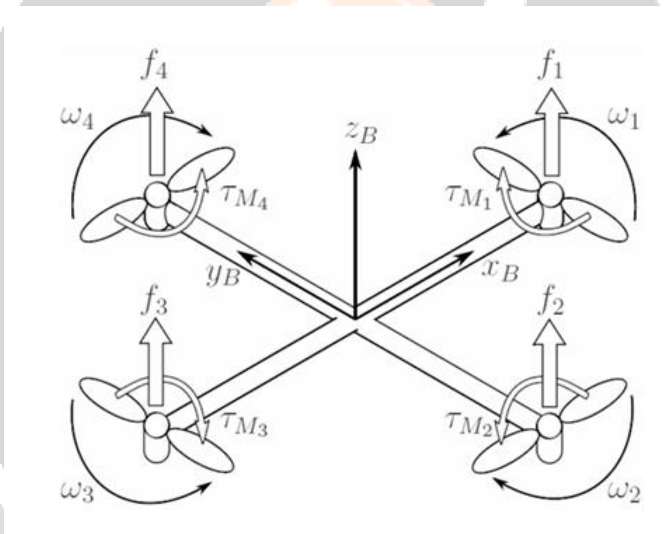

Fig -3.1.1: Quadcopter frame body

For quadcopters, the thrust and moments generated by the rotors are controlled by changing the angular velocities. Equations (1) and (2) express the forces and moments on each propeller:

$$F_i = \times \omega_i^2 \quad (1)$$

$$M_i = K_m \times \omega_i^2 \quad (2)$$

Here, F_i represents the lifting force for each propeller, MiMi is the moment at each propeller, i=1,2,3,4, and K_f and K_m are the aerodynamics force and moment constants, respectively. ω_i denotes the angular speed for each propeller. The moments in the x and y axes are calculated by equations (3) and (4):

$$M_y = (F2-F4) \times L \quad (3)$$

$$M_x = (F1-F3) \times L \quad (4)$$

where L is the length between the two propellers, and mg is the gravity force acting in the opposite direction of the thrust.

Newton's second law is applied to describe linear and rotational motions:

Force= mass × linear acceleration (5)

Torque= inertia ×angular acceleration (6)

When hovering, the forces must balance, as per equation (7):

$$mg=F1+F2+F3+F4 \quad (7)$$

The equation of motion for a hovering quadcopter is represented by equation (8):

$$\frac{m\,\partial^2 r}{\partial t^2} = F1+F2+F3+F4-mg=0 \tag{8}$$

For throttling up and down, equation (9) governs the equations of motion:

$$\frac{M\,\partial^2 r}{\partial t^2} =\{ F_1+F_2+F_3+F_4-mg>0, F>mg \\ F_1+F_2+F_3+F_4-mg<0, F<mg \} \tag{9}$$

Yaw motions are described in equation (10):

$$\frac{m\,\partial^2 r}{\partial t^2}=F_1+F_2+F_3+F_4-mg=0 \tag{10}$$

$$Izz\,\frac{m\,\partial^2 \psi}{\partial t^2} = M_1+M_2+M_3+M_4 \tag{11}$$

where I_{ZZ} is the moment of inertia. The pitch and roll motions involve equations (13), (14), and (15), with the inertia matrix defined in equation (12):

$$I= \begin{matrix} Ixx & 0 & 0 \\ 0 & Iyy & 0 \\ 0 & 0 & Izz \end{matrix} \tag{12}$$

For hexacopters, similar equations govern their motions, with adjustments for the additional rotors. Equation (16) describes the resultant moment for a hexacopter:

$$M=r_1F_1 + r_2F_2 + r_3F_3 + r_4F_4 + r_5F_5 + r_6F_6 \tag{16}$$

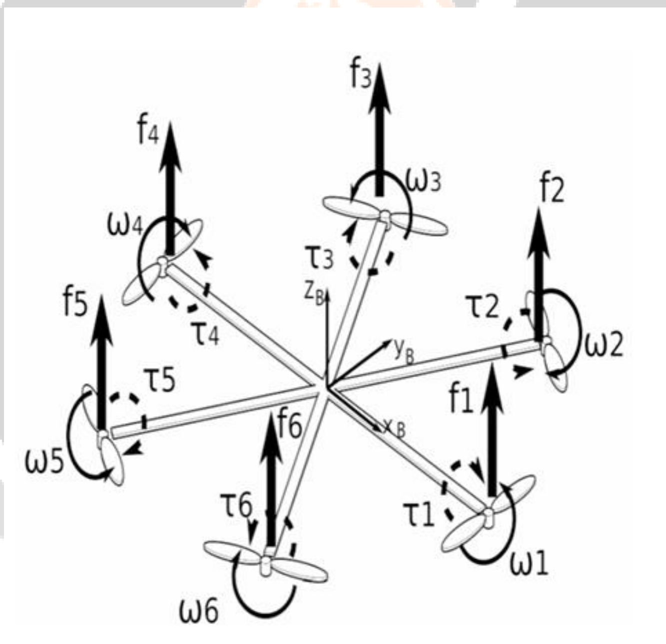

Fig -3.1.2: Hexacopter frame body

The equation of motion for a hovering hexacopter is given as equation (17):

$$\frac{m\,\partial^2 r}{\partial t^2}= F_1+F_2+F_3+F_4\ F_5+F_6+-mg=0 \tag{17}$$

Throttling up and down follows equation (18), while yaw motions are governed by equation (19). Pitch and roll motions involve equation (20), with torques around the roll, pitch, and yaw angles defined in equations (21), (22), and (23):

$$\tau_\phi = \frac{3}{4} K_f r\,(\omega_2^2+ \omega_3^2- \omega_5^2- \omega_6^2) \tag{21}$$

$$\tau_\theta=K_f r(-\omega_1^2-(\omega_2^2/4)+(\omega_3^2/4)+\omega_4^2+(\omega_5^2/4)-(\omega_6^2/4)) \tag{22}$$

$$\tau_\psi = b\,(-\omega_1^2+\omega_2^2-\omega_3^2+\omega_4^2-\omega_5^2+\omega_6^2) \tag{23}$$

These equations highlight how mechanically controlling rotor speeds influences the behaviour and movements of both quadcopter and hexacopter drones, thereby affecting their Radar Cross Section (RCS) signatures.

3.2 UAV Detection Based on Improved YOLOv4 Object Detection Model

1. YOLOv4 Object Detection Model

- Model Overview- Object detection aims to locate objects in images and identify their types. Models are categorized into two types: region-based and end-to-end models. YOLOv4, recognized for its superior performance, is chosen as the base model for UAV detection.
- Architecture Components- The YOLOv4 model comprises three parts: Backbone, Neck, and Head. The Backbone incorporates CSPDarkNet53, characterized by stacked residual blocks. The Neck employs FPN+PAN for feature fusion, enhancing global information. The Head predicts object types and locations using convolutional and fully connected layers.
- Training Strategies- Data Augmentation: Techniques like Random Erasing and CutMix are employed to enhance robustness and increase the quantity of training data. Feature Extraction: The Backbone processes image data, extracting features using CSPDarkNet53, known for its residual block structure conducive to information flow. Feature Fusion: FPN+PAN methods merge multiple feature maps to provide rich global information, aiding in prediction and positioning.
- Prediction Mechanism - The model divides input images into grid cells responsible for generating prediction frames. Each grid cell outputs a vector representing the object's type, position, and confidence. Non-maximum suppression (NMS) is applied to eliminate redundant predictions.

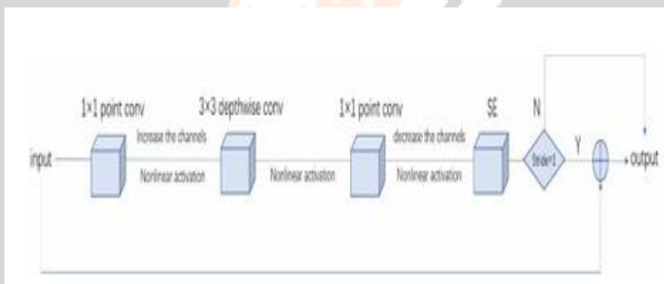

Fig -3.2.1: bneck structure

2. Lightweight Processing

To optimize model efficiency, the MobileNetV3 network replaces CSPDarkNet53 in the Backbone. MobileNetV3 utilizes bneck structures and depth wise separable convolution to reduce parameter count and enhance detection speed.

3. Attention Mechanism Improvement

An attention module is inserted between bneck structures to focus the model on relevant image features. A Channel Attention (CA) module is utilized, enhancing the model's ability to recognize objects by emphasizing prominent features. The reconstructed model, CA-YOLOv4-L, integrates these enhancements to achieve improved detection performance.

3.3 A Novel Approach to Detect Unmanned Aerial Vehicle using Pix2Pix Generative Adversarial Network

1. Pre-processing Module

The pre-processing module consists of five steps:

- Extract UAV Images: Extract images from 98 MPEG4 video files containing UAV footage.
- Resize Images: Resize the extracted images to 256 x 256 resolution.
- Pairing: Select a UAV-less image and pair it with UAV images to create a paired dataset.
- Image Pairing: Resize the paired images to 256 x 512 resolution.
- Data Preparation: Prepare the paired image dataset for input into the Pix2Pix GAN.

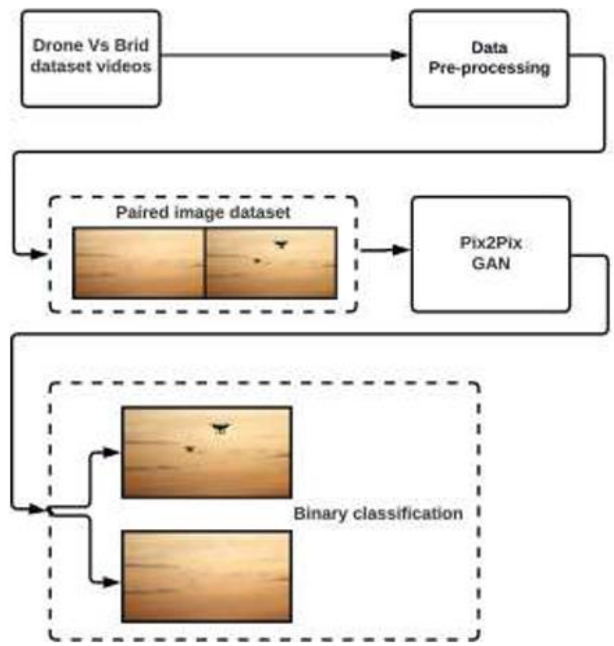

Fig -3.3.1: The system architecture of UAV detection using Pix2Pix GAN

2. Generator Module

The generator module, based on Pix2Pix, utilizes a U-Net architecture. It comprises an encoder and a decoder:

- Encoder: Downsamples input images through eight convolutional blocks, incorporating batch normalization and LeakyReLU activation functions.
- Decoder: Upsamples the encoded features through eight transposed convolutional blocks, also integrating batch normalization and ReLU activation functions. Dropout is applied to the first three decoder blocks to prevent overfitting.

3. Discriminator Module

The discriminator module employs PatchGAN, which assesses real images instead of class vectors:

- PatchGAN: Generates a probability value between zero and one for 70 x 70 pixel patches, predicting the presence of UAVs. It is trained using binary cross-entropy loss, where a matrix with all values set to one indicates the presence of a UAV, and zero indicates its absence.

4. Algorithm for UAV Detection

1. Input: Drone vs. Bird dataset.
2. Output: Predicted output.
3. Pre-processing: Extract images, resize, pair UAV and UAV-less images, and prepare the dataset.
4. Pix2Pix GAN: Utilize the pre-processed dataset as input for the Pix2Pix GAN, comprising generator and discriminator modules.
5. Prediction: Predict the presence of UAVs using the Pix2Pix GAN.

3.4 Extraction of Global and Local Micro-Doppler Signature Features From FMCW Radar Returns for UAVDetection

- **Proposed UAV Detection System:** The proposed UAV detection system is tailored for X-band ground-based surveillance FMCW radars, which aim to address the limitations of existing techniques by excluding time-frequency analysis due to the poor Doppler resolution inherent in X-band surveillance FMCW radar echo signals. The system introduces two novel features: "Number of P-crossing" and "Local Correlation of the m-DS Amplitude Peaks," which are directly extracted from Doppler processing results obtained using the FFT.

- **Radar Signal Processing and Normalization:** Burst selection and Doppler processing are integral steps in the signal processing pipeline. Burst selection involves choosing the representative burst from a series of bursts obtained during radar scans. The chosen burst is subsequently normalized to facilitate further processing. This normalization process involves extracting real and imaginary components from the burst data and adjusting them to maintain consistent mean values across different bursts.

- **Extraction of the Global and Local m-DS Features:** The "Number of P-crossing" feature captures both body-Doppler and m-DS patterns globally, providing insight into the unique characteristics of UAV echoes. Similarly, the "Local Correlation of the m-DS Amplitude Peaks" feature quantifies the similarity between amplitude peaks in Doppler cuts, reflecting the presence of m-DS patterns. These features are computed based on observations made from radar echoes of UAVs and non-UAV objects.

- **Feature-Level Fusion and Feature Normalization:** The extracted features are fused at the feature level through concatenation, resulting in a comprehensive feature vector that encapsulates both global and local information relevant to UAV detection. To ensure consistency and facilitate efficient processing, the feature vector is normalized using the min-max normalization technique, constraining values within a predefined range.

- **UAV Detection Using the TERRM Model:** The feature vector obtained from each burst is employed to train a binary-category classifier using the reduced multivariate polynomial kernel (TERRM). This classifier is optimized to minimize the total error rate, thereby enhancing the system's accuracy in distinguishing UAV echoes from non-UAV signals. The TERRM model's effectiveness in FMCW radar-based UAV detection has been empirically demonstrated.

- **Scan-to-Scan (S2S) Filtering:** To mitigate the impact of noise and ensure stability in the detection process, a scan-to-scan filtering technique is applied. This technique involves associating predicted class labels for the current scan with those from previous scans within the same track. By considering historical data, the system can identify and correct sudden fluctuations in the detection output, thereby improving overall accuracy. This process is illustrated in Figure 3.4.1, depicting the integration of predicted labels across multiple scans to refine the detection results.

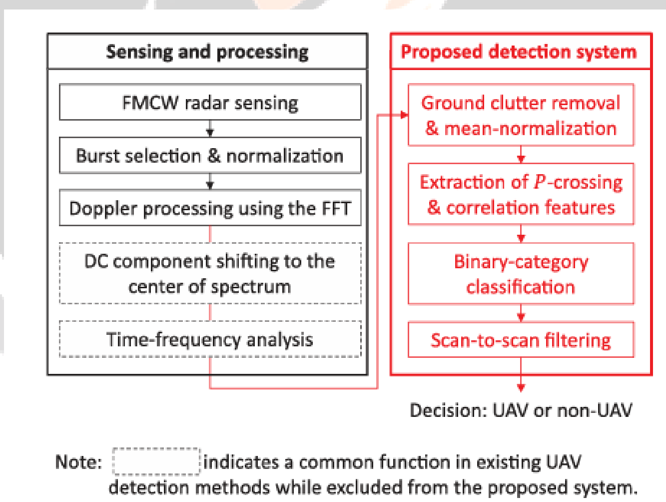

Fig -3.4.1: Overall process of the proposed UAV detection system.

4. CHALLENGES IN UAV DETECTION USING X-BAND GROUND-BASED SURVEILLANCE FMCW RADARS

Poor Doppler Resolution: The primary challenge arises from the inherent limitations in Doppler resolution associated with X-band ground-based surveillance FMCW radars. These radars operate within a specific frequency range (8.0 to 12.0 GHz), which limits their ability to accurately resolve Doppler shifts, particularly when detecting small and fast-moving targets such as UAVs. The narrow bandwidth of these radars results in coarse velocity resolution, making it challenging to distinguish between different moving objects and accurately estimate their velocities.

Signal Processing Complexity: The complexity of signal processing algorithms poses a significant challenge in UAV detection. Extracting meaningful information from radar echoes, especially in environments with high levels of clutter and noise, requires sophisticated processing techniques that are computationally intensive. This includes tasks such as clutter suppression, target detection, tracking, and classification. Designing efficient algorithms that can handle large volumes of radar data in real-time while maintaining high detection accuracy remains a formidable challenge.

Detection of Small Targets: UAVs, particularly small-sized ones, present a detection challenge due to their low radar cross-section (RCS) and erratic movement patterns. Their small size and agile maneuverability make them difficult to detect and track, especially in cluttered environments. Discriminating between UAV echoes and background clutter or other non-UAV objects requires advanced signal processing methods and robust classification algorithms capable of distinguishing between different target signatures.

Variability in UAV Signatures: UAV signatures exhibit variability across different operational scenarios, environmental conditions, and types of UAVs. Factors such as size, shape, material composition, and flight behavior can all influence the radar signature of a UAV. This variability introduces challenges in designing detection algorithms that can adapt to diverse UAV characteristics while maintaining high detection accuracy and reliability. Developing algorithms that can effectively model and classify this variability is essential for robust UAV detection systems.

Noise and Interference: Radar signals are susceptible to various sources of noise and interference, including environmental factors, electromagnetic interference, and clutter from stationary objects. Filtering out such noise while preserving relevant information related to UAV echoes is a non-trivial task. Moreover, mitigating the effects of interference from other radar systems or electronic devices in the vicinity poses additional challenges. Advanced signal processing techniques, adaptive filtering algorithms, and interference mitigation strategies are required to address these challenges effectively.

Real-Time Processing Requirements: In many applications, particularly those involving real-time surveillance and monitoring, there is a stringent requirement for timely detection and response to UAV threats. Meeting these real-time processing demands while maintaining detection accuracy adds another layer of complexity to the design of UAV detection systems. Optimizing algorithms for efficient computation, minimizing processing latency, and ensuring scalability are critical considerations in achieving real-time performance.

Data Anonymization and Privacy Concerns: The use of radar data for UAV detection raises concerns regarding data privacy and anonymity. Radar systems may inadvertently capture sensitive information about individuals or property, raising ethical and legal concerns. Ensuring that sensitive information is adequately protected while still enabling effective UAV detection poses a challenge in system design and implementation. Developing robust data anonymization techniques and adhering to privacy regulations are essential to address these concerns and build trust in UAV detection systems.

5. CLASSIFICATION RESULTS

Impact of Mechanical Control Information on Classification Accuracy:

The classification accuracy of four different drones (MD4-1000 quadcopter, DJIFPV quadcopter, DJI S900 hexacopter, and Black Eagle 50 helicopter) was assessed using eight machine learning (ML) algorithms. These algorithms included three different Convolutional Neural Network (CNN) algorithms, support vector machine, K-nearest neighbors, Naive Bayes, random forest, and decision tree classifiers.

5.1 Effect of Mechanical Control Information:

- When the mechanical control information of drones was not considered, the classification accuracy of ML algorithms decreased.
- ML algorithms performed well when all mechanical control information of drones was considered.

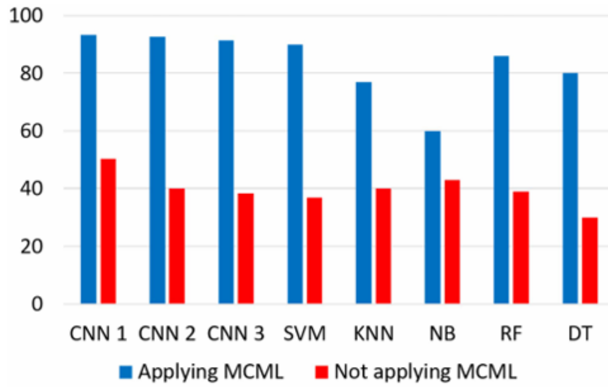

Fig -5.1.1: Different classifiers' accuracy when considering/not considering the mechanical control information of drones.

5.2 Performance of CNN Algorithms (Figure **5.1.1**):

- CNNs demonstrated high accuracy in radar target classification, with DopplerNet, VGG16, and lightCNN algorithms being the most accurate.

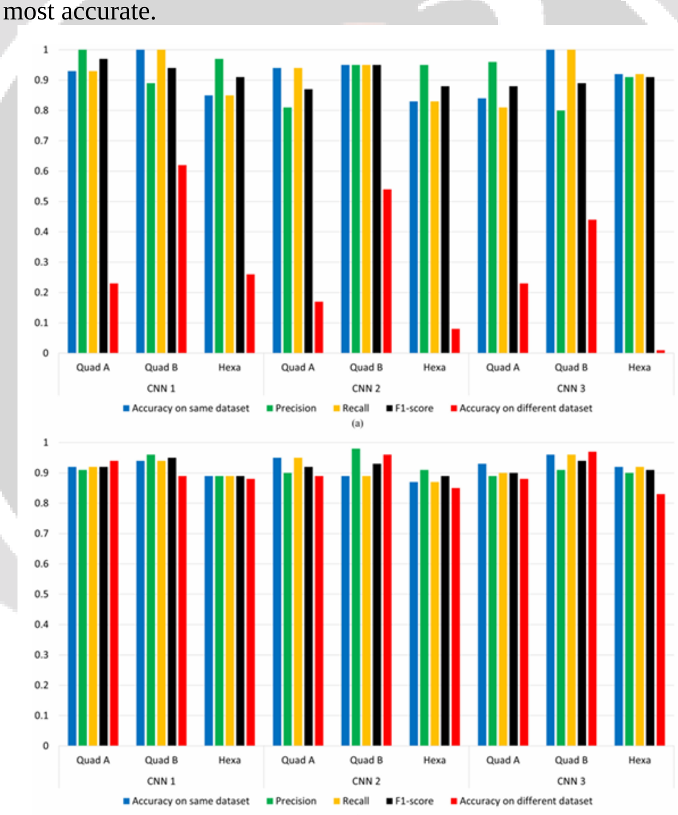

Fig -5.2.1: Comparison of the classification reports for the three different CNN algorithms used in this work when (a) not considering the mechanical control information of drones. (b) Considering the mechanical control information of drones.

5.3 CNN Classification Reports:

- Classification reports for CNN classifiers were analyzed, focusing on quadcopters and hexacopter drones due to the distinctiveness of helicopter drones.
- DopplerNet algorithm showed slightly higher accuracy and was selected for further classification. (Figures 5.2.1 a, 5.2.1 b)

5.4 DopplerNet Algorithm Architecture:

- The DopplerNet algorithm was modified to match RD image dimensions and optimize complexity.
- The architecture consisted of eight layers, including convolutional and dense layers, with hyperparameters set for training. (Figures 5.4.1a, 5.4.1b)

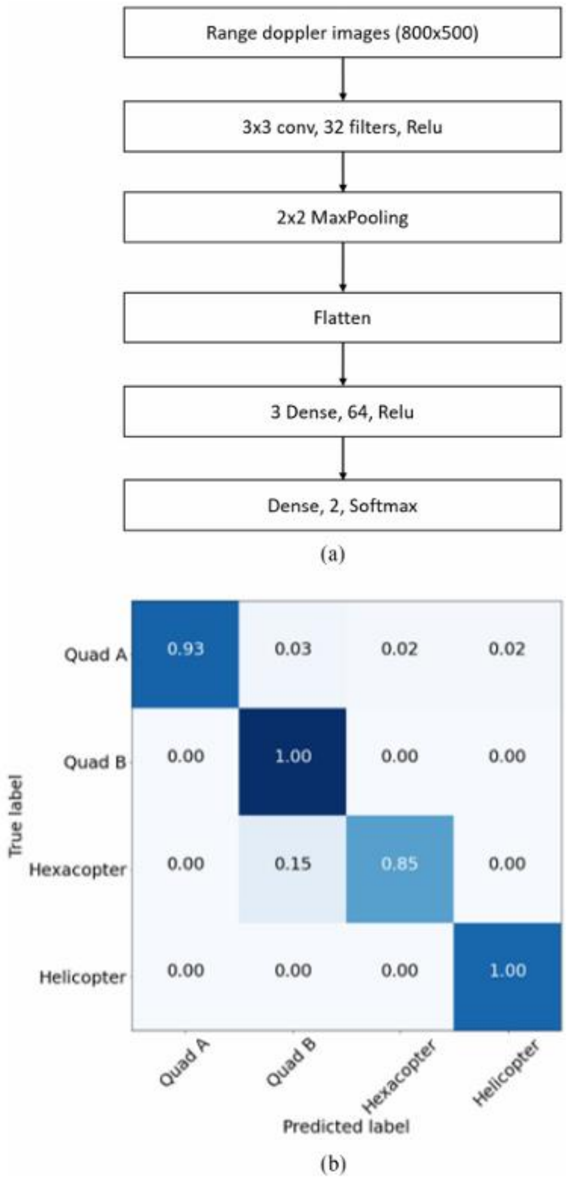

Fig -5.4.1: (a) Flowchart of the DopplerNet CNN algorithm. (b) Its confusion matrix when it was applied to the same dataset.

5.5 Classification Performance:

- The DopplerNet algorithm trained on dataset 1 achieved an accuracy higher than 90%.
- However, when tested on dataset 2, accuracy dropped significantly, highlighting the importance of dataset completeness. (Figures 5.5.1a, 5.5.1b)

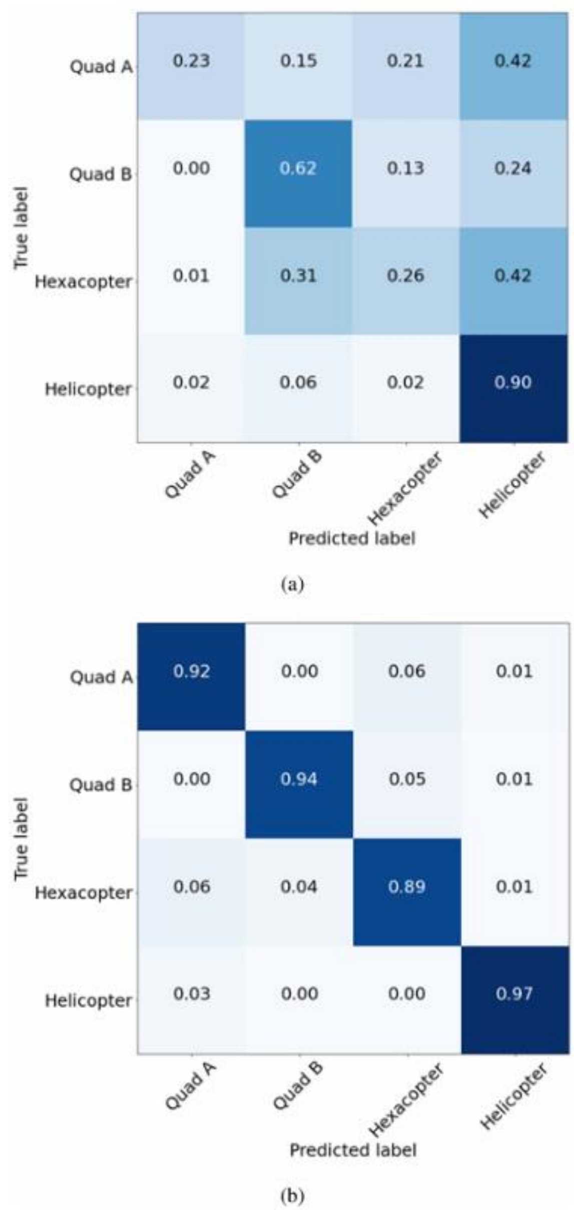

Fig -5.5.1: Confusion matrix for the DopplerNet CNN algorithm when (a) not considering the mechanical control information of drones. (b) Considering the mechanical control information of drones.

5.6 Validation with Additional Datasets:

- Further validation was conducted with dataset 3, which combined datasets 1 and 2, yielding sustained high accuracy.
- A completely different dataset (dataset 4) generated using HFSS was also tested, achieving accuracy exceeding 90%.

5.7 Impact of Mechanical Control on RD Images:

- Investigation using AWR1443BOOST TI radar demonstrated the strong dependence of RD images on mechanical control information of drones.
- RD images obtained for different drone motions underscored the significance of considering mechanical control in classification algorithms.

6. CONCLUSION

In this research paper, we have explored various aspects of UAV detection using X-band ground-based surveillance FMCW radars. Through an in-depth analysis of existing literature and research findings, we have elucidated the challenges faced in UAV detection and discussed novel approaches to address these challenges.

Our investigation has highlighted the significance of micro-Doppler signatures (m-DS) in UAV detection, particularly in capturing unique patterns associated with UAVs. By proposing novel m-DS features, including the number of P-crossing and the correlation of amplitude peaks, we have demonstrated the potential to enhance detection accuracy and reliability.

Furthermore, our review of state-of-the-art techniques, such as machine learning algorithms and signal processing methods, underscores the importance of interdisciplinary approaches in advancing UAV detection technology. By leveraging advancements in radar technology, machine learning, and signal processing, researchers have made significant strides towards improving the efficiency and effectiveness of UAV detection systems.

7. FUTURE SCOPE

Despite the progress made, several avenues for future research exist to further enhance UAV detection capabilities. One promising direction is the integration of advanced machine learning techniques, such as deep learning and reinforcement learning, to optimize classification algorithms and improve real-time detection performance.

Additionally, exploring the synergies between radar-based detection systems and other sensing modalities, such as optical imaging and acoustic sensors, could lead to more comprehensive and robust UAV detection solutions. Fusion of data from multiple sensors can provide complementary information, enabling better detection and tracking of UAVs in various environmental conditions.

Furthermore, addressing challenges related to noise and interference mitigation, as well as improving the scalability and deployment flexibility of UAV detection systems, are crucial areas for future research. Advancements in hardware design, including the development of compact and energy-efficient radar systems, can facilitate the deployment of UAV detection technology in diverse operational scenarios.

In conclusion, this research paper lays the groundwork for further exploration and innovation in UAV detection using X-band ground-based surveillance FMCW radars. By identifying key challenges and proposing avenues for future research, we aim to contribute to the continued advancement of UAV detection technology and its applications in real-world scenarios.

8. REFERENCES

[1]. A. N. Sayed, O. M. Ramahi and G. Shaker, "Machine Learning for UAV Classification Employing Mechanical Control Information," in IEEE Transactions on Aerospace and Electronic Systems, vol. 60, no. 1, pp. 68-81, Feb. 2024,doi:10.1109/TAES.2023.3272303.keywords:{Drones;Quadrotors;Rotors;Radar;Mathematicalmodels;Propellers;Force;Classification;drones;machine learning (ML);radar;range–Doppler (RD);unmanned air vehicle (UAV) control},

[2]. Y. Wang, W. Wei, Z. Xin and D. Li, "Research on Small Face Detection in UAV Command and Control System," 2022 International Conference on Cyber-Physical Social Intelligence (ICCSI), Nanjing, China, 2022, pp. 69-72, doi: 10.1109/ICCSI55536.2022.9970688. keywords: {Command and control systems;Deep learning;Neural networks;Object detection;Autonomous aerial vehicles;Feature extraction;Social intelligence;object detection;computer vision;command and control system;UAV(unmanned aerial vehicle);CNN(convolutional neural network)},

[3]. M. J. Afridi, A. J. Awan and J. Iqbal, "AWG-Detector: A machine learning tool for the accurate detection of Anomalies due to Wind Gusts (AWG) in the adaptive Altitude control unit of an Aerosonde unmanned Aerial

Vehicle," 2010 10th International Conference on Intelligent Systems Design and Applications, Cairo, Egypt, 2010, pp. 1125-1130, doi: 10.1109/ISDA.2010.5687036. keywords: {Unmanned aerial vehicles;Artificial neural networks;Decision trees;Wind;Computer crashes;Machine learning;Intelligent systems;Anomaly Detection;Aerosonde UAV;classification;wind gusts},

[4]. R. Niu, Y. Qu and Z. Wang, "UAV Detection Based on Improved YOLOv4 Object Detection Model," 2021 2nd International Conference on Big Data & Artificial Intelligence & Software Engineering (ICBASE), Zhuhai, China, 2021, pp. 25-29, doi: 10.1109/ICBASE53849.2021.00012. keywords: {Deep learning;Analytical models;Intrusion detection;Object detection;Infrared imaging;Feature extraction;Data models;UAV detection;object detection;lightweight network;attention mechanism},

[5]. V. Balachandran and S. Sarath, "A Novel Approach to Detect Unmanned Aerial Vehicle using Pix2Pix Generative Adversarial Network," 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS), Coimbatore, India, 2022, pp. 1368-1373, doi: 10.1109/ICAIS53314.2022.9742902. keywords: {Vehicle detection;Terrorism;Heuristic algorithms;Media;Generative adversarial networks;Autonomous aerial vehicles;Standards;Unmanned-Aerial-Vehicle (UAV);UAV detection;Pix2Pix Generative Adversarial Networks},

[6]. A. N. Sayed, M. M. Y. R. Riad, O. M. Ramahi and G. Shaker, "A Methodology for UAV Classification using Machine Learning and Full-Wave Electromagnetic Simulations," 2022 International Telecommunications Conference (ITC-Egypt), Alexandria, Egypt, 2022, pp. 1-2, doi: 10.1109/ITC-Egypt55520.2022.9855753. keywords: {Solid modeling;Machine learning algorithms;Radar measurements;Radar detection;Rotors;Radar;Classification algorithms;CNN;Datasets creation;Micro-Doppler signatures;Machine Learning;Range Doppler images;UAV classification},

[7]. S. Gupta, P. K. Rai, A. Kumar, P. K. Yalavarthy and L. R. Cenkeramaddi, "Target Classification by mmWave FMCW Radars Using Machine Learning on Range-Angle Images," in IEEE Sensors Journal, vol. 21, no. 18, pp. 19993-20001, 15 Sept.15, 2021, doi: 10.1109/JSEN.2021.3092583. keywords: {Radar;Chirp;Automobiles;Radar antennas;Drones;Azimuth;Heating systems;Autonomous systems;azimuth angle;elevation angle;enhanced field of view;FMCW radar;heatmap;machine learning;mmWave Radar;YOLO v3},

[8]. K. -B. Kang, J. -H. Choi, B. -L. Cho, J. -S. Lee and K. -T. Kim, "Analysis of Micro-Doppler Signatures of Small UAVs Based on Doppler Spectrum," in IEEE Transactions on Aerospace and Electronic Systems, vol. 57, no. 5, pp. 3252-3267, Oct. 2021, doi: 10.1109/TAES.2021.3074208. keywords: {Doppler effect;Blades;Unmanned aerial vehicles;Rotors;Doppler radar;Dynamics;Tools;Doppler spectrum;drone;joint time–frequency (JTF) image;micromotion;micro-Doppler (MD) effects;small unmanned aerial vehicle (UAV)},

[9]. B. -S. Oh and Z. Lin, "Extraction of Global and Local Micro-Doppler Signature Features From FMCW Radar Returns for UAV Detection," in IEEE Transactions on Aerospace and Electronic Systems, vol. 57, no. 2, pp. 1351-1360, April 2021, doi: 10.1109/TAES.2020.3034020. keywords: {Doppler radar;Doppler effect;Radar detection;Feature extraction;Surveillance;Blades;Frequency modulated continuous wave (FMCW) surveillance radar;micro-Doppler signature analysis;unmanned aerial vehicle (UAV);UAV detection},

[10]. Florez, Jimmy & Ortega, José & Betancourt, Andrés & García, Andrés & Bedoya, Marlon & Botero-Valencia, Juan. (2020). A review of algorithms, methods, and techniques for detecting UAVs and UAS using audio, radiofrequency, and video applications. TecnoLógicas. 23. 269-285. 10.22430/22565337.1408.

[11]. H. Sun, B. -S. Oh, X. Guo and Z. Lin, "Improving the Doppler Resolution of Ground-Based Surveillance Radar for Drone Detection," in IEEE Transactions on Aerospace and Electronic Systems, vol. 55, no. 6, pp. 3667-3673, Dec. 2019, doi: 10.1109/TAES.2019.2895585. keywords: {Doppler effect;Drones;Doppler radar;Surveillance;Signal to noise ratio;Estimation;Doppler resolution;drone detection;ground-based surveillance radar;iterative adaptive approach (IAA);micro-Doppler},