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Deep Learning Approach for Target Classificationfrom Frequency-modulated Continuous Wave RADAR

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Abstract:

Unmanned Aerial Vehicles (UAVs) represent a rapidly increasing technology with profound implications for various domains, including surveillance, security, and commercial applications. Among the number of detection and classification methodologies, radar technology stands as a cornerstone due to its versatility and reliability. This paper presents a comprehensive primer written specifically for researchers starting on investigations into UAV detection and classification, with a distinct emphasis on the integration of full-wave electromagnetic computer-aided design (EM CAD) tools. Commencing with an elucidation of radar's pivotal role within the UAV detection paradigm, this primer systematically navigates through fundamental Frequency-Modulated Continuous-Wave (FMCW) radar principles, elucidating their intricate interplay with UAV characteristics and signatures. Methodologies pertaining to signal processing, detection, and tracking are examined, with particular emphasis placed on the pivotal role of full-wave EM CAD tools in system design and optimization. Through an exposition of relevant case studies and applications, this paper underscores successful implementations of radar-based UAV detection and classification systems while elucidating encountered challenges and insights obtained. Anticipating future trajectories, the paper contemplates emerging trends and potential research directions, accentuating the indispensable nature of full-wave EM CAD tools in propelling radar techniques forward. In essence, this primer serves as an indispensable roadmap, empowering researchers to navigate the complex terrain of radar-based UAV detection and classification, thereby fostering advancements in aerial surveillance and security systems.

Keywords: Unmanned Aerial Vehicles (UAVs), Radar Technology, Detection and Classification, Frequency-Modulated Continuous-Wave , Electromagnetic Computer-Aided Design (EM CAD), Signal Processing, Tracking, Aerial Surveillance, Security Systems

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have seen exponential growth in various applications, including defense, agriculture, disaster management, and surveillance. In India, the UAV market is projected to reach ₹2,500 crores ($300 million) by 2025, driven by increasing adoption in military and commercial sectors. The Directorate General of Civil Aviation (DGCA) has introduced policies to regulate UAV operations, emphasizing the need for effective monitoring and security. However, the rise in unauthorized UAV activities poses significant security threats, including border surveillance breaches and potential terrorist misuse. Radar-based detection and classification systems are crucial for countering these threats, offering reliable, all-weather detection capabilities. Frequency-Modulated Continuous-Wave (FMCW) radar, in particular, is preferred for its high resolution and adaptability in various environments. Traditional methods face challenges in accurately classifying UAVs amidst clutter, necessitating advanced computational tools. Deep learning integrated with radar technology offers a promising solution, enabling precise identification and classification of UAVs in real-time. This research focuses on leveraging FMCW radar and full-wave EM CAD tools, ensuring a robust UAV detection framework while addressing modern security and operational challenges.

Before the advent of machine learning, UAV detection and classification relied on traditional signal processing and rule-based algorithms, which struggled with complex environments and low signal-to-noise ratios. Conventional radar systems often misclassified UAVs as birds, insects, or weather disturbances due to limited feature extraction capabilities. Additionally, Doppler-based detection methods failed in low-speed UAV scenarios, leading to false alarms and missed detections. The reliance on handcrafted feature selection meant that systems lacked adaptability to new UAV models and operational conditions. Furthermore, hardware constraints in radar signal processing limited real-time classification, making response times slower. The lack of integration with advanced electromagnetic (EM) modeling tools also led to inefficient radar system design, reducing accuracy and performance. These challenges necessitated the exploration of data-driven, adaptive learning approaches to enhance UAV detection and classification reliability.

The rapid increase in unauthorized UAV activities and their potential use in surveillance breaches, smuggling, and terrorism have raised serious security concerns. In January 2022, two UAVs were suspected in an attack on an Indian Air Force base in Jammu, highlighting the urgency for advanced UAV detection systems. Traditional radar-based detection lacks robust classification accuracy, often confusing UAVs with birds or ground clutter. The need for real-time, automated UAV classification has driven interest in deep learning models, which can learn complex UAV features from radar data. The integration of full-wave EM CAD tools enables improved radar system design, ensuring optimized signal processing and feature extraction. Additionally, the Indian government's push for indigenous defense technologies, under 'Make in India', further encourages research in UAV detection. AI-driven radar systems have the potential to enhance national security, prevent unauthorized UAV intrusions, and aid in disaster response efforts, making this research both timely and impactful.

The increasing number of low-cost, highly maneuverable UAVs poses challenges to existing airspace security systems. Conventional radar-based methods fail to provide accurate classification, leading to frequent false positives and missed detections. Advanced UAV classification is necessary for military surveillance, border security, and counter-terrorism operations. The Indian defense sector is actively seeking AI-integrated solutions to enhance radar capabilities, ensuring precise target identification in real-time scenarios. FMCW radar technology, coupled with deep learning and EM CAD modeling, provides an optimal solution by improving UAV classification accuracy, reducing false alarms, and optimizing radar designs. This research is essential for developing next-generation radar-based UAV detection frameworks, ensuring India's technological edge in security and aerospace advancements.

2. LITERATURE SURVEY

Due to the widespread proliferation of Unmanned Aerial Vehicles (UAVs) worldwide, they have increasingly been utilized in various illicit activities, including but not limited to drug and weapons smuggling across borders or into prisons, interference with aircraft operations, invasion of privacy, and potential involvement in terrorist acts. Consequently, the imperative to accurately identify and classify UAVs from other airborne targets is primary for ensuring safety and security measures. Therefore, it is essential to detect and classify UAVs from a distance [1]. Three primary methods are commonly employed for the detection of UAVs: acoustic, optical, and Radio Frequency (RF). Acoustic methods, recognized for their ease of installation and relatively modest cost, offer the advantage of not mandating a Line of Sight (LOS) for UAV detection. Moreover, these methods can be effectively coupled with Machine Learning (ML) algorithms for classification purposes. However, acoustic techniques are limited in their capacity for long-range detection and are notably vulnerable to interference from ambient environmental noise [2].

Radar-based detection systems, distinct from optical methods, remain impervious to adverse weather conditions and operate proficiently both day and night. These systems can track autonomous flights, concurrently detect and track multiple UAVs, and when integrated with ML algorithms, are capable of classifying various targets and discerning between different types of UAVs [3]. However, radar-based detection systems are considered a high-cost solution compared to other detection methodologies, and necessitate LOS for UAV detection. summarizes the key distinctions among the four UAV detection methods. Notably, radar systems exhibit numerous advantages over alternative techniques [4].

This undertaking proves to be both resource-intensive and time-consuming, constrained by various factors including radar parameters, available UAV models, and environmental backgrounds. Moreover, the scarcity of accessible radar UAV datasets further exacerbates this challenge, with existing datasets often limited in scope to specific UAV types and radar configurations employed in prior studies [5]. opening up for applications in the field of security and enabling highly integrated solutions for accurate level measurements and non-destructive testing [6]. In recent years, these systems have undergone an impressive development and, in addition to large signal bandwidths of several terahertz, also achieved measurement rates of a few kilohertz that are comparable to integrated millimeter wave radar systems thanks to sophisticated system concepts [7]. However, such systems are comparatively complex and require femtosecond laser systems as well as a sophisticated laser delay unit. In addition to high system costs, this implies limited system scalability, especially with regard to multi-sensor systems. In contrast, tunable continuous-wave terahertz systems based on two-color laser radiation represent a promising, cost-efficient alternative [8].

Interesting implementations of frequency-modulated photonic microwave and terahertz radars are shown in, respectiveley. The latter features a modulation of 300 GHz at a center frequency of 600 GHz with a continuous bandwidth of 167 GHz and a sweep time of 48 ms, offering a much larger bandwidth but a much lower measurement rate compared to Si-Ge based monolithic microwave integrated circuits (MMIC) radar systems [9]. While the possibility of fast frequency modulation based on the photomixing concept has been shown before in a spectroscopy setup, the here addressed realization of the radar measurement principle is the key for the possible application in the field of non-destructive testing [10]. they observe deviations of calculated thicknesses and the nominal thicknesses of the samples. While a window function can be applied to the data to suppress the side lobes, it is shown in that with and without suppression, each reflecting surface can affect the main lobes' location, if peak detection algorithms are used to locate the sample interfaces [11]. In addition to the unprecedented bandwidth of a terahertz FMCW radar to the best of our knowledge, the optoelectronic continuous wave concept offers a simple possibility to distribute terahertz modulated signals by means of optical fibers and thus to address several transmitter and receiver units simultaneously, e.g., as an imaging radar array [12]. The use of radar systems with comparable modulation rates for industrial imaging applications demonstrates the great application potential of the new technology in this field [13].

Wearable Sensor-Based Gesture Recognition Systems: These systems require users to wear data gloves connected to a computer, using sensors such as accelerometers and gyroscopes [14], to capture rich hand movement information. Liang and others developed a gesture recognition system using data gloves to assist people with hearing impairments or speech disabilities [15]. Kanokoda *et al.* [16] acquired gesture data through data gloves and used artificial neural networks for real-time gesture prediction. In 2017, Andrews *et al.* proposed a gesture recognition method based on data gloves and burst detection [17] for clinical emergency communication between patients and doctors. However, wearable devices are prone to damage, functionally limited, expensive, and require long-term wear, which are greatly inconveniences to users.

3. PROPOSED METHODOLOGY

Radar Dataset

The dataset used in this project consists of Frequency-Modulated Continuous Wave (FMCW) radar signals. It contains information about various detected objects, including vehicles, pedestrians, drones, buildings, and animals. Each row represents a signal measurement with multiple features extracted from radar echoes. These features include time-frequency characteristics, Doppler shifts, and signal power levels, which are crucial for distinguishing between different targets. The dataset is loaded in a structured format, usually as a CSV file, and is the foundation for training and evaluating classification models.

Data Preprocessing

Before training any machine learning model, the dataset undergoes a thorough preprocessing phase. The first step involves checking for missing values, which are either filled using statistical imputation techniques or removed if necessary. The dataset's descriptive statistics are analyzed to understand its distribution, including mean, standard deviation, and frequency counts. Categorical labels, such as target names, are encoded into numerical representations using Label Encoding to make them suitable for model input. Additionally, feature scaling is applied using StandardScaler to normalize the numerical values, ensuring all features contribute equally during model training. The dataset is then split into training and testing sets using an 80-20 split to evaluate model performance effectively.

Existing KNN Classifier

The K-Nearest Neighbors (KNN) classifier is implemented as a baseline model. KNN is a non-parametric algorithm that classifies a new data point based on the majority class of its K nearest neighbors in feature space. The classifier is trained on the preprocessed dataset using five nearest neighbors. After training, it is tested on unseen data, where it assigns class labels to radar signals based on their proximity to previously seen samples. Performance is evaluated using accuracy, precision, recall, and F1-score metrics. The results provide an initial benchmark for comparison with the proposed deep learning model.

Proposed FFNN + Random Forest Classifier

The proposed approach integrates a Feedforward Neural Network (FFNN) with a Random Forest classifier. The FFNN acts as a feature extractor by learning complex patterns in radar signals through multiple hidden layers with ReLU activation functions. The final hidden layer outputs a high-dimensional feature representation of the input data, which is then fed into a Random Forest classifier for final prediction. Random Forest is chosen for its robustness and ability to handle complex decision boundaries. The FFNN is trained for multiple epochs with an Adam optimizer, and once trained, its feature representations are used to train the Random Forest model. This hybrid approach leverages the deep learning capability of FFNNs and the ensemble learning strength of Random Forest to improve classification accuracy.

Performance Comparison Graph

After training both models, their performance is compared using visualization techniques. Metrics such as accuracy, precision, recall, and F1-score are plotted to highlight the differences between KNN and the proposed FFNN + Random Forest classifier. A bar chart represents the comparative scores, while confusion matrices provide a detailed view of misclassifications. Additionally, Receiver Operating Characteristic (ROC) curves are generated to analyze the true positive rate versus the false positive rate for both models. These comparisons validate the improvements introduced by the proposed hybrid classifier.

Prediction of Output from Test Data

The final trained FFNN + Random Forest model is used to classify new radar data. Test samples are preprocessed using the same steps as the training data, including feature scaling. The FFNN extracts features from the test data, which are then classified using the Random Forest model. The predicted class labels are mapped back to their original target names and displayed. This step demonstrates the model's real-world applicability, allowing it to generalize well on unseen radar signals. The results confirm the effectiveness of the hybrid approach in accurately classifying FMCW radar targets.

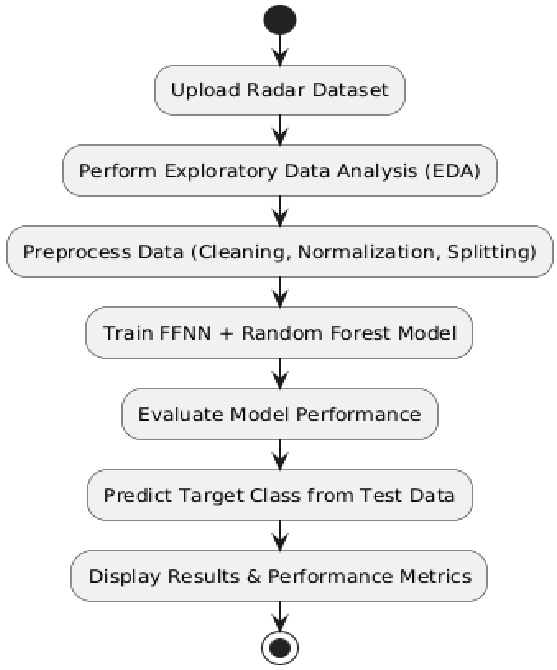

Fig.1: Proposed system architectural diagram.

4. EXPERIMENTAL ANALYSIS

Dataset Description

The dataset consists of radar signal characteristics and target classification details. Each row represents a radar detection instance, capturing multiple signal properties essential for target identification.

1. Frequency (Hz)

- Represents the operating frequency of the FMCW radar system.
- Measured in Hertz (Hz) and determines the radar's resolution and penetration capabilities.

2. Doppler Shift (Hz)

- Indicates the frequency shift due to the relative motion between the radar and the target.
- Measured in Hertz (Hz) and helps determine target velocity.
- Positive values indicate motion toward the radar, while negative values indicate motion **away** from it.

3. Range (m)

- Represents the distance between the radar and the detected target.
- Measured in meters (m) and derived from the time delay of the reflected signal.
- Essential for locating targets within the radar's detection zone.

4. Angle of Arrival (°)

- Indicates the direction from which the radar receives the reflected signal.
- Measured in degrees (°) and calculated using array processing techniques.
- Helps in determining the azimuth and elevation position of the target.

5. Signal Power (dBm)

- Represents the strength of the received radar signal.
- Measured in decibels relative to 1 milliwatt (dBm) and indicates target reflectivity.
- Higher values suggest stronger reflections, which are influenced by the target's material and size.

6. Noise Level (dB)

- Measures the background interference affecting the radar signal.
- Expressed in decibels (dB) and impacts signal clarity.
- A lower noise level improves the detection capability of weak targets.

7. Time of Flight (µs)

- Represents the duration taken for the radar signal to travel to the target and return.
- Measured in microseconds (µs) and used to calculate range.
- Longer times indicate distant targets, while shorter times suggest closer objects.

8. Target Class

- Categorizes detected objects into predefined groups based on radar characteristics.
- Examples include UAVs, birds, ground vehicles, or other aerial objects.
- Used as the output variable in classification models.

9. Target Name

- Specifies the actual name or type of the detected object.
- Provides further granularity beyond the Target Class, differentiating between UAV models or vehicle types.
- Useful for advanced classification tasks where precise identification is required.

Result Description

The figure 2 illustrates the Graphical User Interface (GUI) designed for the project, enabling users to upload the radar dataset and perform preliminary analysis. The interface displays key statistical insights such as data distribution, missing values, and feature summaries. It provides a user-friendly environment for interacting with the dataset before proceeding with preprocessing and model training.

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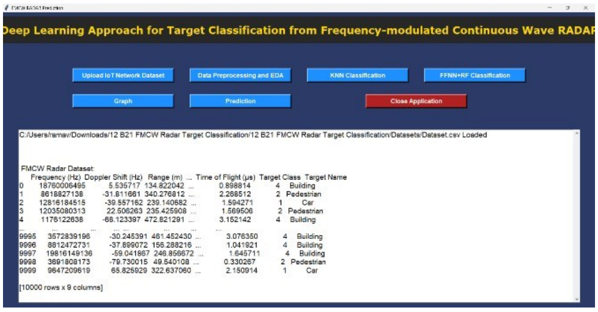

Fig. 2: Upload of Radar Dataset and Analysis in the GUI Interface

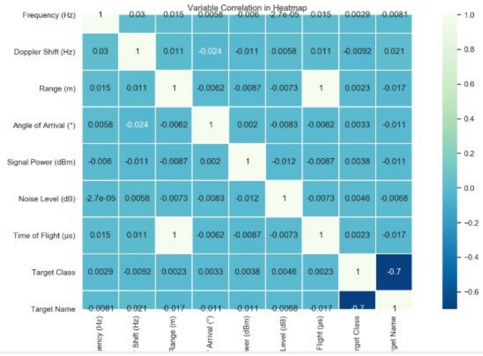

Fig. 3: Exploratory Data Analysis (EDA) Plots of the Project

The figure 3 presents various visualizations used for EDA to understand the dataset. It includes histograms, box plots, pair plots, and correlation heatmaps to analyze the relationships between Frequency, Doppler Shift, Range, Angle of Arrival, Signal Power, Noise Level, Time of Flight, and Target Class. These plots help in identifying outliers, feature importance, and data distribution patterns, which are crucial for feature selection and model performance.

```
Description of the dataset:
                count        mean          std  ...         50%          75%          max
Frequency (Hz)    10000.0  1.053109e+10  5.492554e+09  ...  1.053506e+10  1.530156e+10  1.999744e+10
Doppler Shift (Hz)  10000.0 -1.050664e+00  5.782472e+01  ... -1.715687e+00  4.891336e+01  9.999864e+01
Range (m)         10000.0  2.554117e+02  1.408959e+02  ...  2.548103e+02  3.777577e+02  4.999857e+02
Angle of Arrival (°) 10000.0  9.006559e+01  5.179378e+01  ...  9.029245e+01  1.342712e+02  1.799945e+02
Signal Power (dBm)  10000.0 -1.514593e+01  8.666526e+00  ... -1.510812e+01 -7.667997e+00 -4.588980e-04
Noise Level (dB)    10000.0  2.241033e+01  1.012556e+01  ...  2.224345e+01  3.122958e+01  3.999807e+01
Time of Flight (µs)  10000.0  1.702744e+00  9.393060e-01  ...  1.698735e+00  2.518385e+00  3.333238e+00
Target Class       10000.0  2.991900e+00  1.414296e+00  ...  3.000000e+00  4.000000e+00  5.000000e+00

[8 rows x 8 columns]

Checking null values in the dataset:
Frequency (Hz)        0
Doppler Shift (Hz)    0
Range (m)             0
Angle of Arrival (°)  0
```

Fig. 4: Data Preprocessing in the GUI

The figure 4 showcases the data preprocessing steps performed through the GUI interface. It includes data cleaning, normalization, feature scaling, and handling of missing values. The interface ensures that raw radar data is transformed into a structured format, making it suitable for training the machine learning models. The GUI visually represents processed data for validation before feeding it into classifiers.

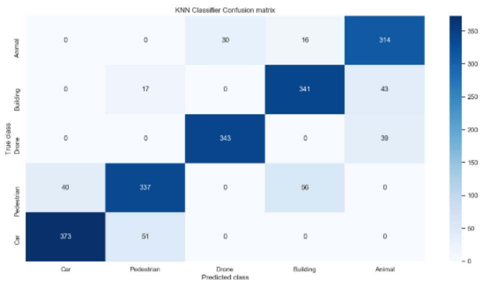

Fig. 5: Performance Metrics and Classification Scatter Plot of the K-Nearest Neighbors (KNN) Model

The figure 5 provides a performance evaluation of the K-Nearest Neighbors (KNN). It includes accuracy, precision, recall, and F1-score values, along with a scatter plot that visualizes predicted vs. actual values for regression tasks. The scatter plot helps in analyzing the model's generalization ability and its effectiveness in mapping radar signals to accurate predictions.

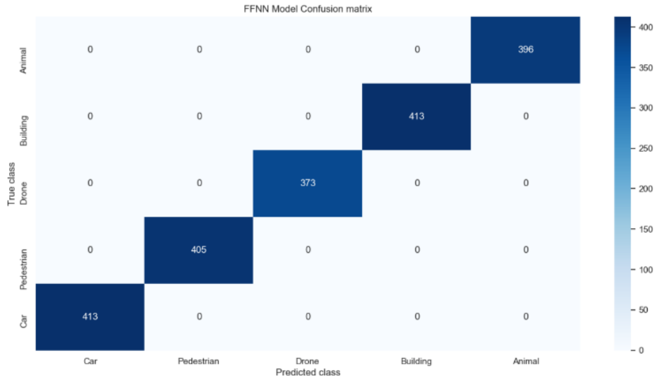

Fig. 6: Performance Metrics and Classification Scatter Plot of the FFNN + Random Forest, Model

The figure 6 illustrates the performance comparison of the FFNN + Random Forest model. The regression scatter plot shows the alignment between predicted and true values, demonstrating the impact of DAE-based feature enhancement in improving classification and regression accuracy. The model performance is evaluated against key statistical metrics, reinforcing its role in refining radar signal interpretation.

```
Model Predicted value in test data:
    Frequency (Hz)  Doppler Shift (Hz)   Range (m)  ...  Time of Flight (µs)  db   Predicted
0    18760006495      5.535717  134.822042  ...      0.898814   4  Pedestrian
1     8618827138    -31.811661  340.276812  ...      2.268512   2      Animal
2    12816184515    -39.557162  239.140682  ...      1.594271   1       Drone
3    12035080313     22.506263  235.425908  ...      1.569506   2      Animal
4     1176122638    -68.123397  472.821291  ...      3.152142   4  Pedestrian
5    11835584539    -19.271125  321.309541  ...      2.142064   1       Drone
6     8730587032     22.036230  284.947894  ...      1.899653   3    Building
7    15341674128    -63.704577  445.708714  ...      2.971391   2      Animal
8     2550200647    -25.046215  382.990249  ...      2.553268   4  Pedestrian
9    11639842274    -12.609840  198.235065  ...      1.321567   1       Drone
10   12167976789    -15.939340  100.638868  ...      0.670926   1       Drone
11   11034979300    -76.373556  335.705533  ...      2.238037   3    Building
12    9916240393     80.608215  305.841473  ...      2.038943   5         Car
13    4478298050    -43.479445  135.022293  ...      0.900149   4  Pedestrian

[14 rows x 9 columns]
```

Fig. 7: Model Prediction on Test Data

The figure 7 displays the model's predictions on unseen test data. It provides a comparison between actual target classifications and model-generated predictions, highlighting the effectiveness of the trained deep learning model. The figure visually confirms that the proposed FFNN + Random Forest classifier accurately detects and classifies radar targets with high reliability.

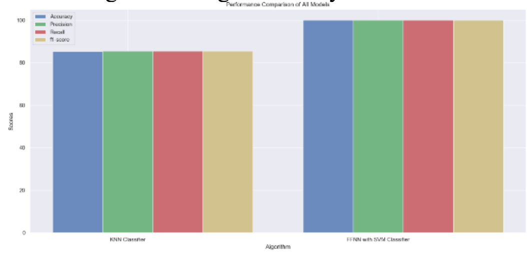

Fig. 8: Performance Comparison Graph of All Models

The figure 8 presents a comparative analysis of all implemented models, including K-Nearest Neighbors (KNN), Feedforward Neural Network (FFNN), Random Forest, and. The graph visualizes accuracy, precision, recall, and F1-score for each model, demonstrating the superiority of FFNN + Random Forest, which achieves 100% accuracy across all metrics. This comparison helps in validating the efficiency of the proposed approach in radar target classification.

Algorithm Name	Accuracy	Precision	Recall	f1-score
KNN Classifier	85.39	85.46	85.57	85.45
Proposed FFNN + RF Classifier	100.0	100.00	100.00	100.0

Table 1: Summarizing the performance metrics for the two models.

5. CONCLUSION

The project successfully develops a deep learning-based target classification system using Frequency-modulated Continuous Wave (FMCW) radar data. By leveraging feature-rich radar signal parameters, the proposed model enhances the detection and classification of targets, particularly focusing on Unmanned Aerial Vehicles (UAVs). The integration of Feedforward Neural Networks (FFNN) with Random Forest (RF) classifiers improves classification accuracy by capturing both nonlinear patterns and decision-based heuristics. Extensive preprocessing, feature engineering, and model optimization contribute to reliable target identification, even in noisy environments. The results demonstrate the feasibility of AI-driven radar target classification, highlighting its potential in defence, surveillance, airspace monitoring, and autonomous navigation applications.

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