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A Random Forest-Based Machine Learning Framework for Radar Target Detection and Classification

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Abstract: *Reliable target detection and classification remain central challenges in modern radar signal processing, particularly as radar systems are increasingly required to distinguish between genuine targets, clutter, and small or low-radar-cross-section objects such as drones. Conventional detection approaches, including constant false alarm rate (CFAR) and threshold-based methods, are well established but can struggle in cluttered or low signal-to-noise-ratio environments where target and clutter statistics overlap. This paper develops and evaluates a Random Forest-based machine learning framework for radar target detection and classification, using features derived from simulated radar returns, amplitude, Doppler shift, signal-to-noise ratio, radar cross-section statistics, and track kinematics, as classifier inputs. A labelled synthetic dataset of 6,000 target and clutter returns, generated with realistic statistical overlap between classes, was used to train and evaluate a Random Forest classifier, tuned via grid search and 5-fold stratified cross-validation, benchmarked against a conventional amplitude-only CFAR detector calibrated to a comparable false-alarm operating point. On a held-out test set of 1,800 samples, the Random Forest classifier achieved 90.4% accuracy, 90.9% precision, 89.8% probability of detection, an F1-score of 0.903, and an area under the ROC curve of 0.960, compared with 62.7% accuracy and 37.0% probability of detection for the CFAR baseline at a matched false-alarm rate. Doppler shift and track velocity were identified as the most influential features in the trained model. These results indicate that a Random Forest classifier incorporating kinematic and radar cross-section features can substantially outperform amplitude-only CFAR detection under overlapping target/clutter conditions, while remaining considerably less computationally demanding than deep learning alternatives reported in the literature.*

Keywords: *Radar Target Detection; Machine Learning; Random Forest; Radar Signal Processing; Target Classification; CFAR.*

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I. INTRODUCTION

Target detection is one of the most fundamental functions of a radar system, requiring reliable discrimination between genuine targets and background clutter, noise, and interference. Traditional radar processors rely on constant false alarm rate (CFAR) detectors and moving target indication (MTI) or moving target detection (MTD) algorithms, which use statistical hypothesis testing against a modelled noise or clutter distribution. While computationally efficient and well understood, these methods can perform poorly when clutter statistics are non-stationary or when target and clutter returns overlap in amplitude and Doppler space.

Machine learning has increasingly been applied to radar target detection and classification as an alternative or complement to conventional statistical detectors. Liu, Xu, and Chen (2021) demonstrated that a random forest model trained on motion-characteristic features extracted from surveillance radar data could reliably distinguish between bird and drone targets, outperforming simpler statistical classifiers on this discrimination task.

A micro-Doppler signature is like a unique fingerprint produced by the tiny movements of an object, like the flapping wings of a bird. Park, Lee, Park, and Kwak (2021) also used CNNs; their research converted radar signals into spectrograms instead of using micro-Doppler signatures directly, producing images that show how the signal changes over time and frequency. The CNN analysed these images and was able to identify drones with high accuracy, which shows that machine learning-based classifiers can differentiate between real target and clutter information that conventional or traditional methods cannot easily detect. Ensemble methods such as Random Forest have several practical advantages: they do not need much data, they do not require much computing power, and they are easier to train than deep learning models like CNNs, while remaining robust to noisy, redundant, or incomplete features. This study uses features like amplitude, Doppler, and radar cross-section (RCS) statistics. This study develops a Random Forest-based framework for radar target detection and classification, trains and tests it using simulated radar data, and compares its performance with the traditional CFAR detector in order to determine if Random Forest can detect and classify radar targets more accurately than the conventional radar detection method.

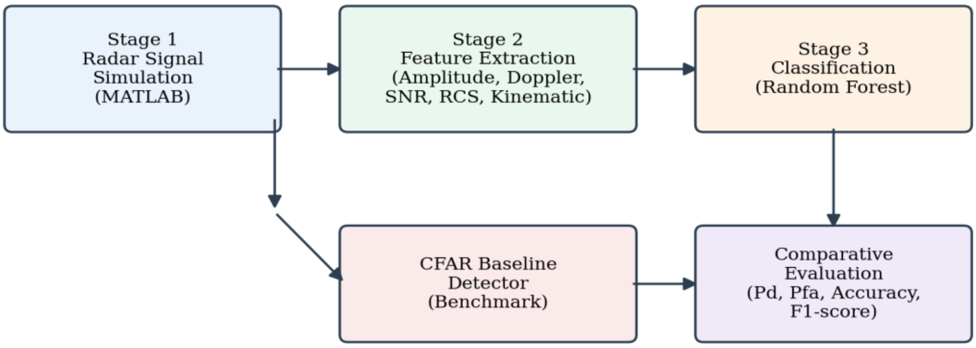

Figure 1. Random Forest-Based Radar Target Detection and Classification Architecture

II. REVIEW OF RELATED LITERATURE

A. Machine Learning Approaches to CFAR and Detection Thresholding

There has been a lot of research recently on the use of machine learning directly to help CFAR detect radar targets. The traditional method of detecting an object using radar only detects an object and then classifies it as a separate step. Recent studies combine both processes by allowing machine learning to assist detection itself, which makes the entire process more intelligent and accurate.

Cao et al. (2022) developed a Deep Neural Network (DNN) to improve CFAR detection in high-resolution FMCW radar. Their model analysed peak sequences, which are patterns formed by strong radar echoes that may represent real targets. The DNN learned to differentiate between real targets and clutter, especially in non-homogeneous clutter, where the surrounding environment changes from one location to another, compared to the traditional method of detection.

Da Costa et al. (2023) used a Deep Neural Network; instead of manually estimating the characteristics of the clutter, the neural network learned them automatically from nearby range-Doppler cells, which contain information about the distance and speed of surrounding objects. The study applied the high-frequency surface-wave radar method, which is used for monitoring ships and coastlines. Their findings showed a detector that behaved like CFAR but performed better than most traditional CFAR methods in a non-homogeneous clutter environment, with the advantage that the model did not need prior knowledge of the clutter distribution because it learned the clutter behaviour directly from the radar data.

Perďoch et al. (2024) similarly used a simple neural network, but in a different way. Instead of replacing CFAR, the neural network was placed before the conventional radar detector as a pre-processing stage to clean or improve the radar signal before CFAR analysed it. This method reduced the effects of radar clutter and also made the detection process faster. The study also showed that machine learning does not necessarily have to replace traditional radar detection methods, but can work with existing techniques like CFAR to improve their performance.

B) Ensemble and Deep Learning for Radar Target Classification

Machine learning is used beyond radar detection; many studies also use it to classify radar targets after the radar has already detected that a target is present. Once a possible target is found, the machine learning determines what the target actually is, such as a drone, aircraft, ship, or bird. Jiang et al. (2021) developed a Convolutional Neural Network (CNN) for radar target detection and compared it with the traditional matched-filter method, which detects targets by comparing received radar signals with a known reference signal. The CNN performed better, especially when the signal-to-noise ratio (SNR) was low. Coşkun and Bilicz (2023) carried out a study that focused on classifying different target shapes. It used radar cross-section (RCS) information, which measures how much radar energy an object reflects. Their study converted raw RCS data into histograms. The study was carried out using near-field millimetre-wave radar, which operates over short distances using very high-frequency radio waves. The histogram representation helped the radar detection system differentiate between targets with different shapes.

In another study, Coşkun and Bilicz (2024) compared traditional machine learning algorithms with a deep learning Neural Network (DNN) for classifying radar targets using RCS data. Their study showed that Random Forest, a traditional machine learning algorithm, achieved results that were almost as good as the deep neural network. Random Forest required much less training data than the deep learning model, which is very consistent with the results obtained in this paper.

Radar target classification research has also applied machine learning to Synthetic Aperture Radar (SAR) images. Zhang et al. (2022) incorporated an attention mechanism into a CNN, which helps the neural network focus on the most important part of an image instead of treating every part equally; this improved the ability to differentiate between targets that looked very similar in SAR images.

Zhang and Zhang (2022) proposed a study focused on classifying ships in SAR images. Their study combined several kinds of radar features instead of relying on only a single feature-type classifier. These included a polarization fusion network and geometric features, which describe the shape and structure of the target. The study found that combining multiple feature types of radar features produced more accurate and reliable classification than using a single feature type, which is the same principle applied in this paper. Instead of relying on a single radar measurement, this study combines several features like amplitude, Doppler, radar cross-section (RCS), and kinematic features.

C. Micro-Doppler and Human/UAV Activity Classification

Another area of radar research uses machine learning with micro-Doppler signatures to identify human movements and drones. Chakraborty et al. (2022) used a Deep Neural Network (DNN) to analyse micro-Doppler radar signals. Their goal was to identify unusual or suspicious human activities. Noori et al. (2021) used deep learning with Ultra-Wideband (UWB) radar data to classify human activities. Their study showed that deep learning could accurately identify human activities even when the environment changed. Qiao et al. (2022) addressed a similar problem of radar receiving signals from several moving objects at the same time; for instance, multiple people moving together can create overlapping micro-Doppler patterns. Their research focused on separating these mixed signals so that each activity could be identified correctly. This problem is similar to radar target detection, because a real target signal may overlap with unwanted signals from clutter. Papadopoulos and Jelali (2023) reviewed several machine learning-based radar human activity recognition studies. They found that the quality of the features extracted from radar data was very important. This finding supports the feature-importance analysis in this paper, where it is examined which radar features contribute most to accurate target detection and classification.

D) Automotive and Broader Radar Object Detection

Machine learning-based radar target detection has also been widely used in automotive radar systems, such as those in self-driving cars and advanced driver-assistance systems (ADAS), where CFAR-only methods have limitations. For instance, on a busy road where there are many vehicles, pedestrians, buildings, and other objects, CFAR may struggle to differentiate real targets from clutter. Decourt et al. (2022) developed a deep learning radar detector for automotive applications. Their study was directly on range-Doppler maps, a radar image that shows the distance of the objects from the radar (range) and their speed (Doppler). The deep learning model learned patterns directly from these maps to detect vehicles and road objects. Srivastav and Mandal (2023) conducted a review on many studies on deep learning for autonomous-driving radar. Their study found that machine learning methods consistently performed better than traditional CFAR detectors. This was especially true in cluttered urban environments, where the radar system must detect objects among traffic, buildings, and pedestrians; machine learning was better at differentiating real objects from background clutter. Although deep learning produced better detection results, it was computationally expensive; this paper addresses this problem by using Random Forest, which is a lightweight ensemble learning method rather than a deep neural network. This makes Random Forest a more suitable algorithm for use in systems with limited computing resources.

E. Rationale for an Ensemble Learning Approach

Using all the literature reviewed so far, from Raval et al. (2021) and other previous studies, there is a trade-off between deep learning and Random Forest. Deep learning models can often achieve a higher target recognition accuracy, which means they are very good at detecting radar targets correctly. However, they usually require a large amount of training data, powerful computers, and take longer to train and run, while Random Forest is an ensemble machine learning method that has several practical advantages, such as needing less training data, less computing power, and being faster and easier to train. Jiang et al. (2023) reviewed automatic radar target detectors and confirmed that this balance between higher accuracy and lower computational cost is a common finding in radar machine learning studies. Based on the findings from previous studies, this paper evaluates the Random Forest algorithm empirically against a CFAR detector; this study chooses to use the Random Forest algorithm because it provides a good balance between performance and computational efficiency. The study uses a simulated radar-return dataset, which contains computer-generated radar signals, and then compares its performance with the traditional CFAR detector, which serves as the baseline or reference method.

Table 1. Summary of Reviewed Literature

Author(s) & Year	Technique	Application Domain	Key Finding
Liu, Xu, & Chen (2021)	Random Forest	Bird/drone classification	RF outperformed simpler statistical classifiers using motion features
Park et al. (2021)	CNN	UAV classification (spectrogram)	Reliable drone classification from radar-derived spectrograms
Jiang, Ren, Liu, & Leng (2021)	CNN	Radar target detection	Outperformed matched-filter detection at low SNR
Cao et al. (2022)	DNN (peak-sequence)	CFAR detection, FMCW radar	Improved detection consistency in non-homogeneous clutter
Da Costa et al. (2023)	DNN (CFAR-like)	HF surface-wave radar	Outperformed conventional CFAR without prior clutter model
Perďoch et al. (2024)	Simple neural network	Clutter suppression (pre-CFAR)	Reduced clutter impact and processing time
Coşkun & Bilicz (2023, 2024)	RF vs. DNN (RCS features)	RCS-based target classification	Classical ML competitive with DNN, lower data needs
Zhang et al. (2022)	CNN + attention	SAR automatic target recognition	Improved discrimination of similar target classes
Zhang & Zhang (2022)	Polarization fusion network	SAR ship classification	Multi-feature fusion improved robustness
Chakraborty et al. (2022)	DNN	Human activity (micro-Doppler)	Reliable suspicious-activity recognition
Noori et al. (2021)	Deep learning	Human activity (UWB radar)	Reliable classification across environments
Qiao et al. (2022)	Signal separation + ML	Overlapping micro-Doppler signals	Improved separation of simultaneous activities
Papadopoulos & Jelali (2023)	Comparative review	Radar human-activity recognition	Feature quality drives performance more than architecture
Decourt et al. (2022)	Deep object detector	Automotive radar (range-Doppler)	Effective detection directly on range-Doppler maps

Author(s) & Year	Technique	Application Domain	Key Finding
Srivastav & Mandal (2023)	Review	Autonomous-driving radar	Learning-based detectors outperform CFAR in clutter, at higher cost

III. PROBLEM STATEMENT

Conventional or traditional CFAR-based radar detection is vulnerable to false alarms, and it also misses detections in cluttered or low signal-to-noise environments (Cao et al., 2022; Da Costa et al., 2023). Existing machine learning-based radar detection research is focused on either large labelled datasets (Jiang et al., 2023) or deep learning algorithms that require very large amounts of training data and powerful computers, consume more memory, and take longer to train (Raval et al., 2021; Rojhani et al., 2023; Srivastav & Mandal, 2023). There are limited studies that evaluate lightweight ensemble classifiers, such as Random Forest, for radar detection using simulated datasets in research and training environments without the use of high-performance computing infrastructure. This study addresses the gap in knowledge by developing and empirically evaluating a Random Forest-based detection and classification framework using a simulated radar-return dataset, to evaluate its performance and compare it directly with the traditional CFAR detector baseline.

IV. METHODOLOGY

A. Radar Signal Simulation

A labelled simulated radar dataset was created. It contained 6,000 radar returns made up of 3,000 target samples and 3,000 clutter or non-target samples, and it was generated in Python using the NumPy library. The simulated data were created using statistical distributions that represent the target and clutter radar returns. The target amplitude, Doppler shift, and Radar Cross Section (RCS) were generated from a statistical distribution with a higher central tendency than the clutter values. The target data was not perfectly clean but had deliberately wide variance and random measurement noise added to each feature, which made the simulated data more realistic, so that the target signals and clutter signals overlap substantially and the machine learning model cannot simply separate them using a single rule; this creates the difficulty in detection encountered in cluttered and low signal-to-noise ratio (SNR) radar environments.

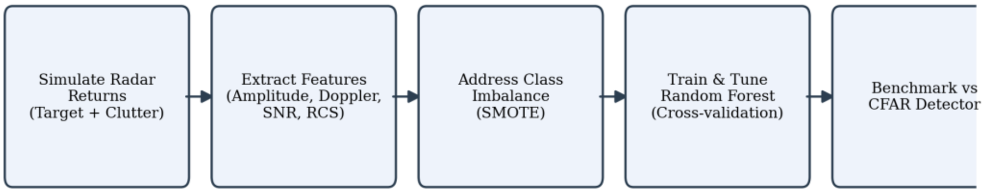

Figure 2. Research Methodology Workflow

B. Feature Extraction

Radar features were selected based on previous studies on radar classification (Liu et al., 2021; Coşkun & Bilicz, 2023). Each simulated radar return was described using seven different features, listed in Table 2, which came from different categories of radar information such as amplitude, Doppler, signal-to-noise ratio (SNR), radar cross-section (RCS), track velocity, and trajectory consistency. These enabled the model to gain a more complete description of each radar target. Liu et al. (2021) also demonstrated a motion-related features approach to differentiate between target classes using radar cross-section (RCS) values.

Table 2. Radar-Return Feature Set Used for Classification

Feature	Domain	Description
Signal amplitude	Time domain	Peak/mean return amplitude per detection
Doppler shift	Frequency domain	Estimated radial velocity from Doppler frequency
Signal-to-noise ratio (SNR)	Statistical	Return power relative to local noise/clutter floor
Radar cross-section (RCS) mean	Statistical	Mean RCS estimate per detection

Feature	Domain	Description
Radar cross-section (RCS) std. dev.	Statistical	RCS fluctuation across returns
Track velocity	Kinematic (multi-scan)	Estimated speed from successive detections
Trajectory consistency	Kinematic (multi-scan)	Smoothness/predictability of track path (0–1)

C. Model Development and Evaluation

The dataset was split into a training set (4,200 samples), which was 70% of the dataset, and a test set (1,800 samples), which was 30% of the dataset, using stratified sampling in order to retain class balance. A Random Forest classifier was trained with different values for its hyperparameters; the number of trees, maximum tree depth, and minimum leaf size were tuned using grid search under 5-fold cross-validation, and the model that achieved the highest F1-score, which balanced precision and recall, was selected. The best configuration selected was 200 decision trees, a maximum tree depth of 10, and a minimum leaf size of 1. This configuration gave the highest F1-score during cross-validation and was chosen for the final model.

To give a fair comparison, the study also used a traditional CFAR-style detector that served as the baseline; the CFAR detector made decisions using only amplitude (signal strength). Before testing the CFAR detector, the study adjusted its detection threshold using the training data, so that the detector would produce a false alarm rate of about 10% on clutter samples. The threshold was then applied directly, unchanged, to the test dataset to ensure the evaluation was fair and unbiased.

V. SYSTEM ARCHITECTURE

The model is divided into three stages, shown in Figure 1. The first stage is the simulation stage; in this stage, labelled radar data is generated, as explained in Section IV(A). The second stage is the feature-extraction stage; in this stage, the features listed in Table 2 are extracted from each simulated radar signal. The third stage is the classification stage; in this stage, the trained Random Forest model analyses the extracted features and makes a final decision to produce a target or non-target label, with its performance compared with the traditional CFAR baseline. Both methods are tested using the same test dataset, which makes the comparison fair, following the pre-processing-stage integration pattern of Perďoch et al. (2024). This simple design helps the machine learning model to be evaluated, or improved on, as a direct substitute for the traditional CFAR detection method under the same radar simulation environment.

VI. RESULTS AND DISCUSSION

After training the Random Forest model, it was tested on 1,800 simulated radar returns, and the classifier achieved 90.4% accuracy, 90.9% precision, an 89.8% probability of detection (Pd), an F1-score of 0.903, and a false alarm rate (Pfa) of 9.0%, with an area under the ROC curve (AUC) of 0.960. The 5-fold cross-validation used on the training set produced a consistent mean accuracy of 90.7%, with a variation of only ±0.7%, which indicates that the model performed almost the same across every test group rather than a result specific to a single train/test split. The majority of targets whose amplitude overlapped with the clutter distribution were missed by the amplitude (signal strength)-only CFAR baseline.

The traditional CFAR detector was compared with the Random Forest model; its false-alarm rate was adjusted to a level similar to the Random Forest model, and its performance (11.7% Pfa on the test set) achieved an accuracy of 62.7% and a significantly lower detection probability of 37.0%, which missed the majority of target signals because the amplitude overlapped with the clutter distribution. Table 4 and Figure 3 show the summary of these results; Figure 4 shows the confusion matrices.

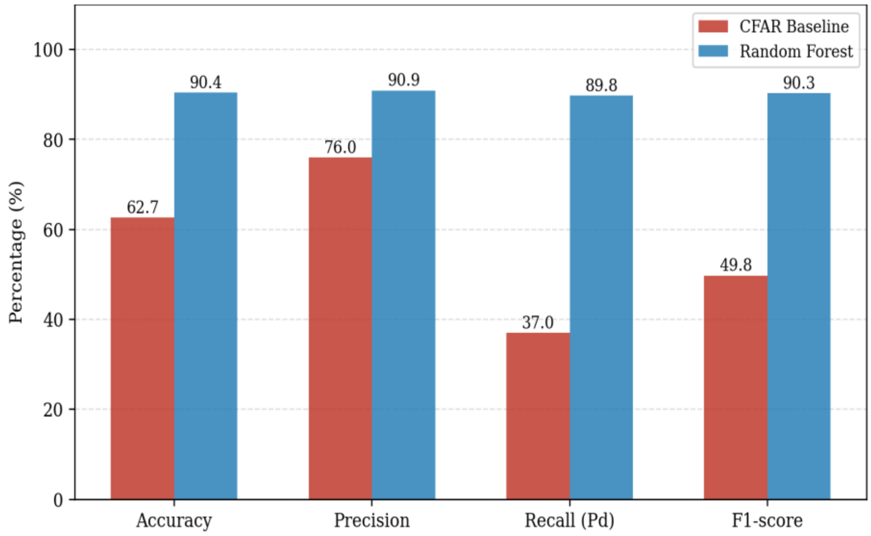

Figure 3. Random Forest vs. CFAR Baseline Performance on the Simulated Test Set

Table 4. Comparative Performance: Random Forest vs. CFAR Baseline

Metric	CFAR Baseline	Random Forest
Accuracy	62.7%	90.4%
Precision	76.0%	90.9%
Recall / Probability of Detection (Pd)	37.0%	89.8%
False-alarm rate (Pfa)	11.7%	9.0%
F1-score	0.498	0.903
AUC	— (single operating point)	0.960

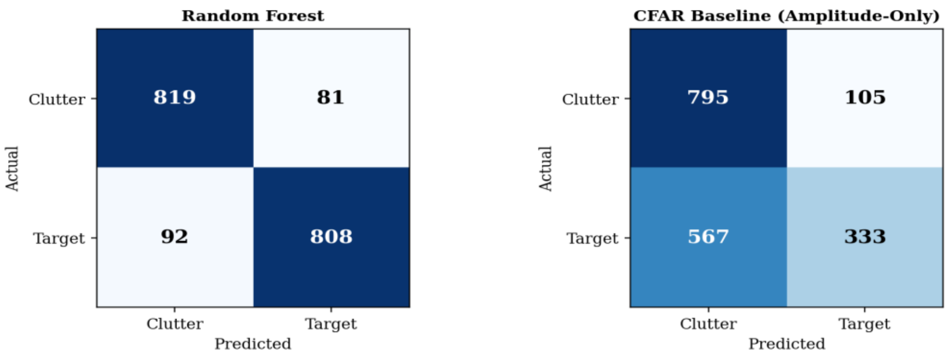

Figure 4. Confusion Matrices – Random Forest and CFAR Baseline (Test Set, n = 1,800)

The largest performance gap between the Random Forest model and the CFAR detector is in the ability to detect real targets. The CFAR baseline (signal strength) missed 567 out of 900 real targets in the test set. That is, a 63% miss rate, which is very high, because a large share of the simulated target returns had amplitude values similar to clutter signals. The Random Forest classifier performed much better because it used all seven radar features and missed only 92 out of 900 real targets. These results are consistent with the finding of Papadopoulos and Jelali (2023), which postulates that feature-extraction quality is often more important than using a very complex machine learning model. Their study showed that adding features such as Doppler information (target speed) and kinematic information (how the target moves over time) can greatly improve performance compared with using amplitude alone.

Figure 5 shows the ROC (Receiver Operating Characteristic) curve for the Random Forest classifier with the CFAR detector operating point. Comparing both methods at about the same false-alarm rate, the CFAR operating point lies well below the Random Forest ROC curve, which agrees with the quantitative results presented in Table 4.

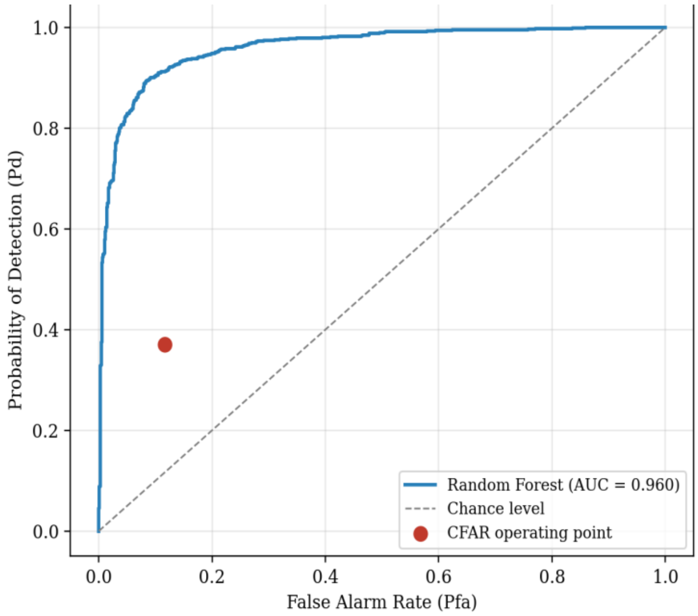

Figure 5. ROC Curve – Random Forest Classifier vs. CFAR Operating Point

Figure 6 shows the feature importance scores produced by the Random Forest model. The feature importance tells us how each radar feature contributed to the model's decisions. The Random Forest model found that some radar features were more useful than others. The most important features were Track Velocity (0.249) and Doppler Shift (0.235), followed by Trajectory Consistency (0.196), Amplitude (0.124), and mean Radar Cross Section, RCS (0.112). The least important features were Signal-to-Noise Ratio, SNR (0.054) and RCS standard deviation (0.031).

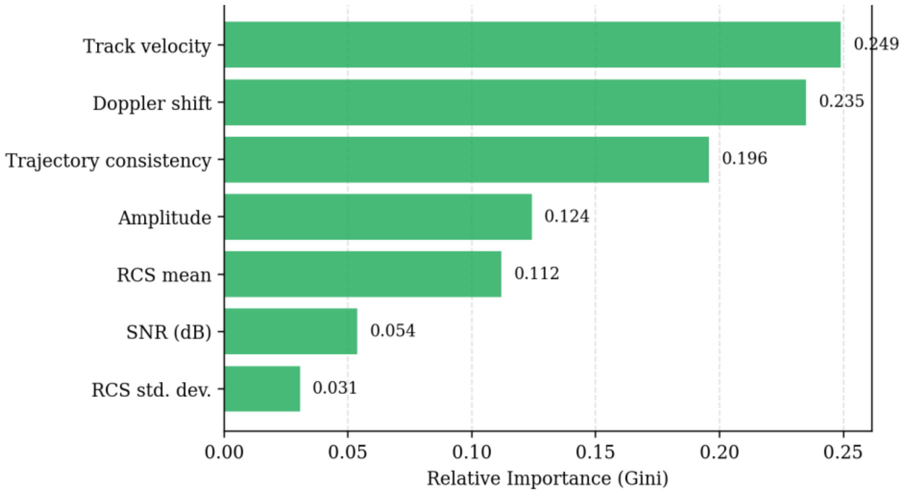

Figure 6. Random Forest Feature Importance

This feature importance shows that kinematic and Doppler information were more valuable than amplitude. They are only available through multi-scan tracking or frequency-domain processing, which analyses changes in the radar signal frequency. These results also explain why the traditional CFAR detector underperformed on this dataset.

The results of this study are consistent with the findings of Liu et al. (2021) and Coşkun and Bilicz (2024), although not exactly the same magnitude. Their study showed that ensemble machine learning methods like Random Forest performed better than traditional methods based on amplitude or fixed thresholds, especially when kinematic information and Radar Cross Section (RCS) features are available.

The Random Forest model achieved an excellent performance, with an area under the curve (AUC) of 0.960 and a cross-validated accuracy of 90.7%. These results were achieved using a lightweight model with 200 decision trees and a maximum tree depth of 10, that trains in a few seconds on standard computer hardware, which supports the idea that ensemble learning like Random Forest offers a practical and lower-cost effective alternative to deep learning models for radar target detection. The results from the study were obtained using a simulated radar dataset with statistically modelled radar returns, rather than using actual radar systems.
In future research, the study should test the Random Forest model using real radar measurements or a hardware-in-the-loop system (combining computer simulations with real radar hardware).

VII. CONCLUSION

Traditional CFAR-based radar target detection method performs very poorly, especially in environments with heavy clutter or when the amplitude of real targets behaves like that of clutter. To address this problem, this study developed a Random Forest machine learning framework for radar detection and classification using a simulated radar-return dataset. The results showed that the model performed better than the conventional CFAR detector. The Random Forest model achieved 90.4% accuracy and 89.8% probability of detection, while the CFAR detector achieved 62.7% accuracy and 37.0% probability of detection at the same false-alarm rate.

These findings are consistent with the study of Liu et al. (2021), Raval et al. (2021), Cao et al. (2022), Da Costa et al. (2023), Rojhani et al. (2023), Fraser et al. (2023), Coşkun and Bilicz (2024), Perďoch et al. (2024), and Jiang et al. (2023), which shows that machine learning methods can improve radar target detection and classification by making use of more radar information than traditional CFAR methods. Unlike deep learning models, the Random Forest algorithm requires less training data, less computing power, and can be trained quickly while still achieving high performance. This makes the proposed framework suitable for universities, research laboratories, and training environments where access to real radar systems, large labelled datasets, or high-performance computers may be limited.

A limitation of this study is that the model was tested using simulated radar data rather than measurements collected from a real radar system. Future work should validate the model using real radar or hardware-in-the-loop data and extend the framework to classify multiple target types instead of only distinguishing between targets and clutter.

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