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An Intelligent Radar Signal Intelligence Framework for Automated Impairment-Aware Classification

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Abstract

Radar signal classification plays a vital role in modern surveillance, defense, electronic warfare, and communication systems by enabling the identification of different radar modulation types under varying signal conditions. Traditionally, radar signal analysis has been performed manually by domain experts through visual inspection and interpretation of signal patterns, which is time-consuming, labor-intensive, and highly dependent on human expertise. Such manual approaches become increasingly ineffective when dealing with large volumes of impaired radar signals affected by noise, interference, and low Signal-to-Noise Ratio (SNR) conditions. The need for an automated and intelligent classification system has therefore become essential to improve accuracy, speed, and reliability in radar signal recognition tasks. This project proposes a machine learning-based framework for the classification of impaired radar signals using image preprocessing, feature extraction, and predictive modeling techniques. Radar signal images are resized and transformed into feature vectors through pixel-based feature extraction, creating a structured dataset suitable for classification. Two machine learning models, namely Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost), are employed and evaluated for radar signal prediction, with XGBoost serving as the final prediction model due to its superior classification performance. The proposed system automatically identifies different radar signal categories from previously unseen samples and generates accurate predictions. The significance of this work lies in its ability to reduce manual effort, enhance classification efficiency, support real-time signal intelligence applications, and provide a scalable solution for reliable radar signal recognition in complex operational environments.

Keywords: Radar Signal Classification, Impaired Radar Signals, Machine Learning, SNR, Image Preprocessing, Predictive Modeling, Signal Intelligence.

1. Introduction

Radar technology has become a fundamental component of numerous modern applications, including air traffic management, military surveillance, weather monitoring, maritime navigation, and intelligent transportation systems. Its capability to detect, locate, and monitor objects in diverse environmental conditions makes it indispensable for both civilian and strategic operations. Despite these advantages, radar systems frequently encounter performance degradation caused by various signal impairments such as background noise, multipath propagation, atmospheric disturbances, electromagnetic interference, and equipment-related distortions. These impairments can alter the characteristics of received signals, making accurate interpretation and classification increasingly difficult. As radar deployments continue to expand and generate larger volumes of data, conventional signal analysis approaches struggle to maintain the required levels of precision, speed, and operational efficiency.

The increasing complexity of radar environments has created a strong demand for intelligent computational techniques capable of automatically identifying and categorizing radar signal patterns. Feature extraction serves as a critical stage in this process by transforming raw radar signal representations into meaningful numerical features that capture discriminative information. Machine Learning (ML) algorithms utilize these extracted features to learn underlying relationships among different signal categories and make reliable predictions on previously unseen samples. Unlike manual

10.48047/jocaaa.2024.33.05.82

interpretation methods that rely heavily on expert knowledge and extensive analysis time, ML-based systems can process large datasets efficiently while adapting to complex signal variations. This capability significantly improves the robustness and consistency of radar signal classification under challenging operating conditions.

To address these challenges, this project presents an automated framework for the classification of impaired radar signals using feature extraction and supervised learning techniques. Radar signal images are preprocessed, resized, and converted into feature vectors that represent the essential characteristics of each signal class. The extracted features are utilized to train SVM and XGBoost classifiers, enabling the system to distinguish among multiple radar signal categories with high accuracy. By leveraging data-driven learning and automated decision-making, the proposed approach enhances classification performance, minimizes human intervention, supports rapid signal analysis, and contributes to the development of reliable radar intelligence systems for real-world operational environments.

2. Literature Survey

Z. Ma et al. [1] proposed a radar waveform recognition framework for Low Probability of Intercept (LPI) radar signals by utilizing multiple image-based representations of radar data. The study transformed radar waveforms into different visual formats through time-frequency analysis and extracted discriminative features from these images to improve classification performance. The proposed approach effectively captured signal characteristics that are difficult to identify using conventional signal analysis methods and demonstrated enhanced recognition accuracy under noisy and interference-prone environments. M. Gupta et al. [2] investigated the major challenges associated with emitter classification in electronic warfare systems. The authors emphasized that accurate identification of radar emitters is essential for effective threat assessment and strategic decision-making. Their work discussed the limitations of traditional signal processing approaches and highlighted the growing importance of intelligent classification techniques capable of handling complex and rapidly evolving electromagnetic environments. P. Bezousek et al. [3] presented a comprehensive overview of radar technology development and its progression from conventional analog architectures to advanced digital radar platforms. The study examined various technological innovations that significantly enhanced radar performance, including improvements in signal processing, detection range, target resolution, and system reliability. The authors also discussed the expanding role of radar systems in both military and civilian applications. Z. Qu et al. [4] introduced a radar signal recognition method based on Singular Value Entropy (SVE) and fractal dimension analysis. Their approach focused on extracting complexity-related information from radar signals to distinguish between multiple waveform categories. By combining entropy measurements with fractal characteristics, the proposed model effectively captured nonlinear signal properties and achieved improved classification performance, particularly in challenging signal conditions.

W. Xie et al. [5] explored the application of deep learning techniques for digital modulation recognition using High-Order Cumulants (HOCs). The research demonstrated that deep neural networks can automatically learn complex statistical relationships from signal data without extensive manual feature engineering. The utilization of HOCs enabled the extraction of detailed signal characteristics, resulting in improved recognition accuracy and stronger resistance to noise and signal distortions. X. Chang et al. [6] developed a novel methodology for sorting and classifying unknown radar emitter signals. The proposed system combined advanced signal processing mechanisms with machine learning strategies to analyze signal attributes and group previously unseen emitters into meaningful categories. The study highlighted the importance of adaptive recognition systems for modern electronic warfare scenarios where new radar threats emerge continuously. D. Zeng et al. [7] proposed an automatic radar modulation classification technique utilizing the Rihaczek Distribution (RD) and Hough Transform (HT). The method generated informative time-frequency representations of radar signals and applied pattern

10.48047/jocaaa.2024.33.05.82

recognition procedures to identify modulation patterns accurately. Experimental analysis demonstrated that the framework maintained robust classification performance even in environments affected by Doppler shifts and multipath propagation effects. J. Lunden et al. [8] presented a statistical framework for automatic radar waveform recognition capable of classifying radar signals without human intervention. Their methodology integrated time-frequency signal analysis with statistical pattern recognition algorithms to extract meaningful waveform features. The proposed framework improved recognition reliability across diverse operational scenarios and contributed toward the development of intelligent and autonomous radar systems.

M. Zhang et al. [9] investigated the recognition of LPI radar waveforms using Time-Frequency Distribution (TFD) analysis. The authors extracted representative signal characteristics from time-frequency representations to improve the detection and identification of weak radar emissions. Their results demonstrated that TFD-based feature extraction significantly enhances classification accuracy in low Signal-to-Noise Ratio (SNR) environments where conventional approaches often fail. D. Sahraeian et al. [10] proposed a manifold-based framework for crosslingual and multilingual speech recognition. The study utilized the underlying geometric structure of speech data to improve recognition performance across multiple languages. By exploiting common speech characteristics shared among different linguistic systems, the approach achieved enhanced recognition accuracy while reducing the need for extensive language-specific retraining. R. Sarikaya et al. [11] investigated the use of Deep Belief Networks (DBNs) for Natural Language Understanding (NLU) applications. Their research demonstrated that DBNs can effectively learn hierarchical language representations and capture complex semantic relationships within speech data. The proposed approach significantly improved the performance of speech recognition and language modeling tasks in conversational and noisy environments. J. Fan et al. [12] introduced Hierarchical Deep Multi-Task Learning (HD-MTL) for large-scale visual recognition applications. The framework enabled multiple related recognition tasks to be learned simultaneously within a unified deep learning architecture, facilitating efficient knowledge sharing across tasks. Experimental results showed notable improvements in recognition accuracy, feature generalization capability, and scalability when handling large and diverse image datasets.

3. Proposed System

The system architecture is designed to automate the recognition and classification of radar signal modulation types using machine learning techniques. The process begins with the acquisition of radar signal images from multiple modulation categories, followed by image preprocessing and feature extraction to convert visual information into numerical representations. The extracted features and corresponding labels are stored and organized for further analysis. Feature visualization techniques are employed to understand data distribution and category balance before model training. Subsequently, Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost) classifiers are trained and evaluated using the prepared dataset. Various performance metrics such as accuracy, precision, recall, and F1-score are computed to assess model effectiveness. Based on comparative analysis, the best-performing classifier is selected for final prediction of unseen radar signal samples, as illustrated in Figure 1.

Step 1: Radar Signal Data Acquisition

The system starts by collecting radar signal images from multiple modulation categories such as CPFSK, GFSK, and B-FM. These images are organized into separate folders representing their respective classes. Proper categorization ensures efficient data management and supports supervised learning. The collected dataset serves as the foundation for model development and evaluation.

Step 2: Image Preprocessing and Feature Extraction

10.48047/jocaaa.2024.33.05.82

The acquired radar signal images undergo preprocessing operations to standardize the input data. Each image is resized to a fixed dimension to reduce computational complexity and maintain consistency throughout the dataset. The resized images are then flattened into numerical feature vectors representing signal characteristics. These extracted features form the input dataset for machine learning models.

Step 3: Data Storage and Feature Analysis

The generated feature vectors and their corresponding class labels are stored for future use and faster processing. If previously processed data exists, the system directly loads the saved arrays instead of repeating preprocessing operations. Data visualization techniques such as count plots and tabular analysis are employed to examine class distribution and dataset characteristics. This step helps in understanding data quality before model training.

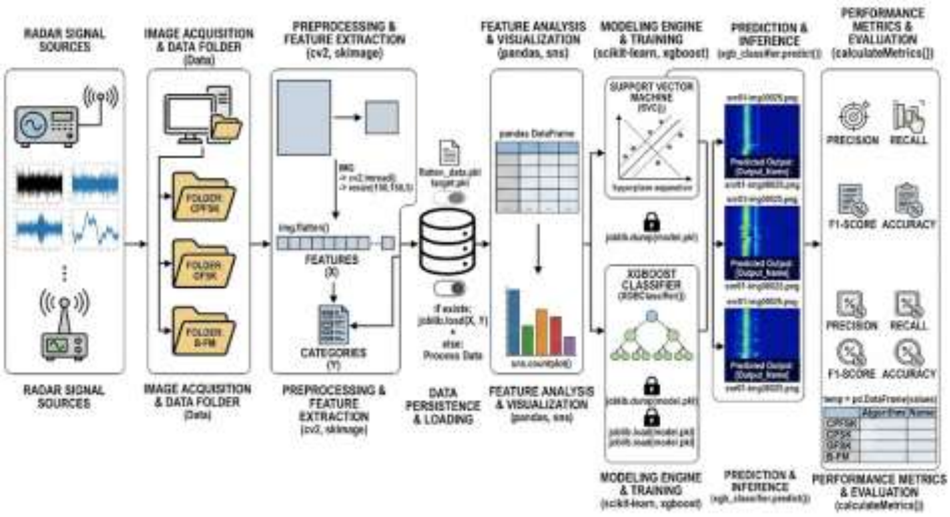


Figure 1: Proposed system architecture

Step 4: Model Training and Classification

The prepared dataset is divided into training and testing subsets for model development. Two machine learning classifiers, namely Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost), are trained using the extracted signal features. The SVM classifier learns optimal decision boundaries between classes, while XGBoost utilizes boosted decision trees to improve classification performance. Both models are stored after training for future prediction tasks.

Step 5: Prediction and Inference

Once the models are trained, unseen radar signal images are provided as input for classification. The images undergo the same preprocessing and feature extraction procedures before prediction. The trained classifiers analyze the extracted features and assign the most appropriate modulation category to each signal sample. The predicted class labels are displayed as the output of the system.

Step 6: Performance Evaluation and Model Comparison

The effectiveness of the trained classifiers is assessed using performance metrics including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive evaluation of classification performance across different signal categories. Comparative analysis is performed to identify the classifier that delivers the most reliable results. The final performance summary assists in selecting the most suitable model for radar signal classification applications.

10.48047/jocaaa.2024.33.05.82

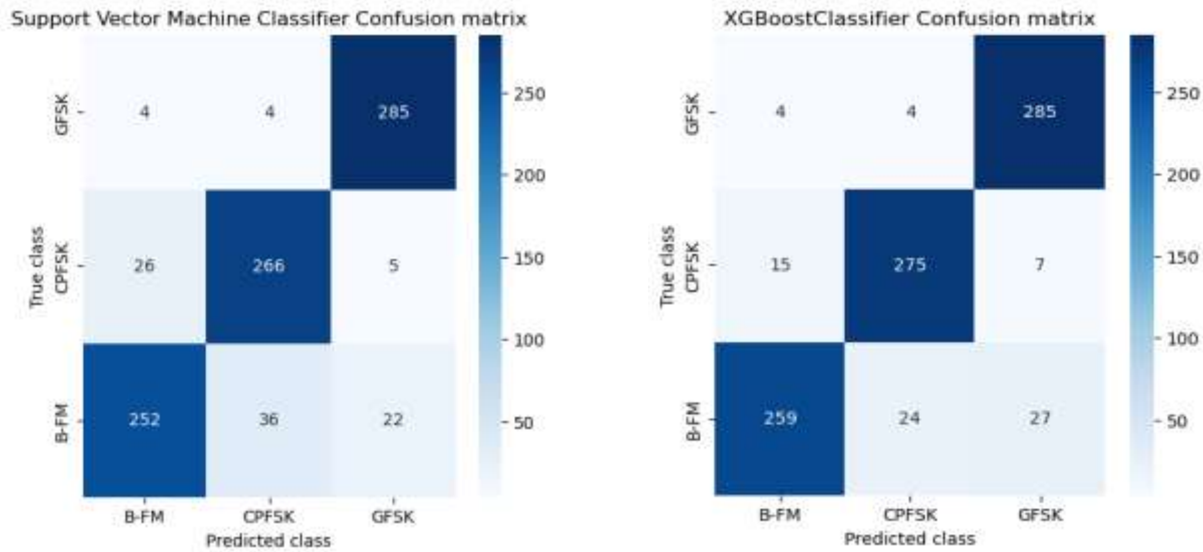
3.1 XGBoost Classifier

XGBoost is an advanced machine learning technique based on gradient boosting. It is known for its high performance and scalability, making it suitable for a variety of predictive modeling tasks, including the classification of mango leaf diseases.

How XGBoost Works:

1. **Boosting Framework**: XGBoost builds models in a sequential manner, where each new model corrects the errors made by the previous models. It combines the predictions of multiple weak learners (typically decision trees) to produce a strong predictive model.
2. **Gradient Descent Optimization**: The algorithm uses gradient descent to minimize a loss function. It calculates the gradient (or derivative) of the loss function concerning the predictions and adjusts the model parameters to improve the accuracy of predictions.
3. **Regularization**: XGBoost includes regularization techniques to prevent overfitting. It applies L1 (Lasso) and L2 (Ridge) regularization to the loss function, which helps in improving model generalization and performance.
4. **Feature Importance**: XGBoost also provides insights into feature importance, which helps in understanding the contribution of each feature to the model's predictions.
5. **Parallelization**: The algorithm is designed to be efficient and can perform computations in parallel, making it faster and capable of handling large datasets effectively.

4. Results Description



(a) (b)

Figure 2: Confusion Matrix of (a) SVC and (b) XGBoost Classifier

Figure 2(a) illustrates the confusion matrix of the SVC model for radar signal classification. The classifier correctly identified 266 CPFSK, 285 GFSK, and 252 B-FM signal samples, as indicated by the diagonal elements of the matrix. However, several samples were incorrectly assigned to other modulation categories, particularly within the B-FM class. The distribution of values demonstrates that the model learned the distinguishing characteristics of the radar signals reasonably well. Overall, the confusion matrix reflects the capability of the SVC model to perform effective modulation classification with satisfactory prediction accuracy.

10.48047/jocaaa.2024.33.05.82

Figure 2(b) depicts the confusion matrix of the XGBoost Classifier for radar signal classification. The model successfully classified 275 CPFSK, 285 GFSK, and 259 B-FM samples, indicating strong recognition performance across all signal categories. Compared to the SVC model, the XGBoost Classifier achieved a higher number of correctly classified samples and fewer misclassifications in certain classes. The dominant diagonal values confirm the classifier's ability to accurately distinguish between different modulation types. These results demonstrate the robustness and superior predictive performance of the XGBoost model for radar signal recognition.

Figure 3 depicts a sample radar signal image belonging to the B-FM modulation category along with the corresponding prediction generated by the XGBoost Classifier. The figure demonstrates how the trained model analyzes the visual characteristics of the radar signal and accurately assigns it to the appropriate modulation class. The successful prediction of the B-FM signal indicates that the classifier has effectively learned the distinctive patterns present in the training data. This result highlights the model's capability to generalize well to previously unseen signal samples during the testing phase. The accurate classification further validates the effectiveness of the XGBoost model in radar signal recognition and supports its suitability for practical signal identification applications.

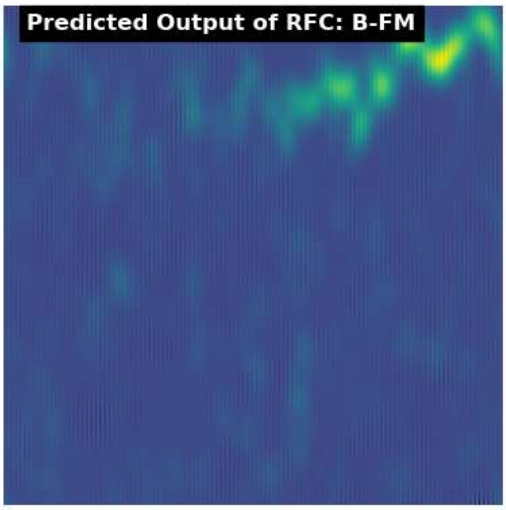


Figure 3: Predicted Output for B-FM Signal

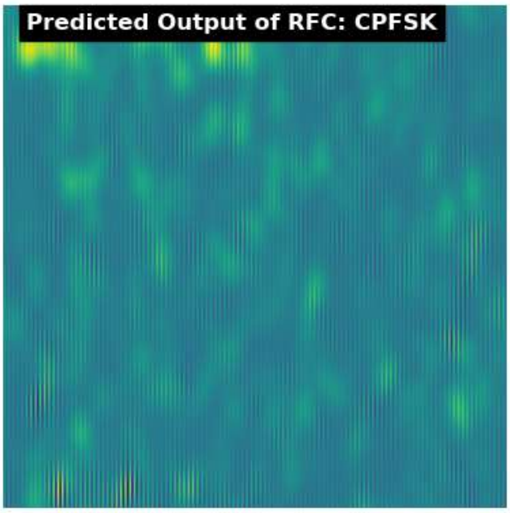


Figure 4: Predicted Output for CPFSK Signal

Figure 4 illustrates a sample radar signal image belonging to the CPFSK modulation category together with the prediction generated by the XGBoost Classifier. The figure demonstrates the model's ability to

10.48047/jocaaa.2024.33.05.82

accurately recognize the unique characteristics and modulation patterns associated with CPFSK signals. The successful prediction indicates that the classifier has effectively learned discriminative features from the training dataset and can generalize well to unseen signal samples. The accurate classification result highlights the robustness and reliability of the XGBoost model in distinguishing CPFSK signals from other modulation types. This outcome further validates the effectiveness of the proposed classification framework for real-time radar signal recognition and intelligent signal analysis applications.

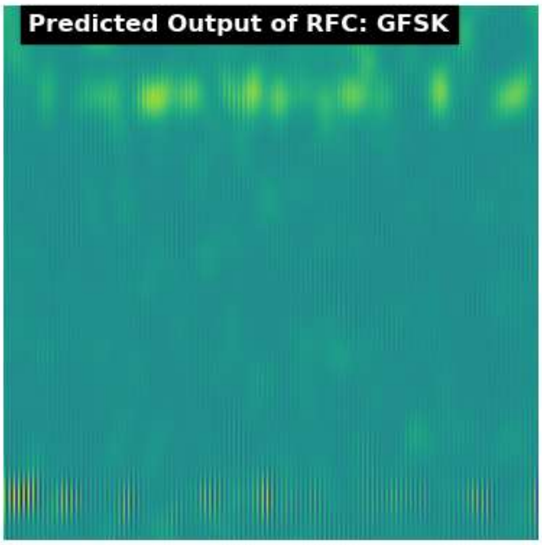


Figure 5: Predicted Output for GFSK Signal

Figure 5 depicts a sample radar signal image corresponding to the GFSK modulation category along with the prediction generated by the XGBoost Classifier. The figure demonstrates the model's capability to accurately identify the distinctive modulation characteristics present in GFSK signals. The correct classification indicates that the trained model has successfully learned meaningful signal patterns and can effectively differentiate GFSK from other radar signal categories. The prediction result highlights the consistency and robustness of the classifier when processing previously unseen test samples. The accurate recognition of the GFSK signal further confirms the reliability and effectiveness of the XGBoost model for radar signal classification under diverse operational scenarios.

5. CONCLUSION

The research successfully enhances the classification of impaired radar signals by leveraging advanced feature extraction techniques and machine learning models. By addressing the limitations of traditional methods, such as threshold-based and manual approaches, the research demonstrates significant improvements in both accuracy and robustness of radar signal classification. The implementation of machine learning algorithms, particularly the XGBoost classifier, has proven to be effective in processing and classifying radar signals in real-time, which is critical for applications in aerospace, defense, meteorology, and automotive industries. The project not only automates the classification process but also reduces the reliance on manual analysis, thereby increasing efficiency and decision-making speed in critical operations. The extensive testing and validation performed in this project confirm the adaptability of the models to various types of impairments and operational conditions, making them reliable and versatile for real-world applications.

10.48047/jocaaa.2024.33.05.82

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