ML Approach for Classification of Impaired Radar Signals using Feature Extraction

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ABSTRACT

Many different industries, including aerospace, defense, meteorology, and automotive, rely heavily on radar systems for their numerous applications. On the other hand, these systems frequently experience signal impairments as a result of noise, interference, and signal deterioration, which can put their accuracy and reliability at risk. As a result, the purpose of this study is to improve the classification of degraded radar signals by utilizing sophisticated approaches for feature extraction and machine learning (ML). Traditional methods, such as threshold-based, statistical approaches, and manual analysis, have a limited capacity to deal with the complexity and diversity of radar signal impairments. As a result, these methods frequently result in inadequate performance and flexibility. In the approach that has been described, significant features are extracted from radar signals in order to capture their fundamental characteristics. This is then followed by the deployment of powerful machine learning algorithms for categorization. Real-time processing and classification of damaged signals is the purpose of these techniques, which are designed to facilitate quick decision-making and response in applications that are of crucial importance. The proposed system utilizes XGBoost for the classification of impaired radar signals by leveraging advanced machine learning-based feature extraction techniques. The extracted features are then fed into an XGBoost classifier, which efficiently learns patterns in the impaired radar signals and categorizes them based on the type of degradation. XGBoost's gradient boosting mechanism, feature importance ranking, and ability to handle noisy data improve the classification accuracy, ensuring real-time and reliable decision-making for critical radar-based applications.

Keywords: Radar signals, Feature extraction, Machine learning, XGBoost model.

1. INTRODUCTION

Radar systems are integral to various sectors, including aerospace, defense, meteorology, and the automotive industry, due to their ability to detect and track objects over considerable distances under varying conditions. However, these systems are susceptible to signal impairments, such as noise, interference, and signal degradation, which can severely impact their performance. According to a report by the Federal Aviation Administration (FAA), radar signal impairments contributed to approximately 12% of aviation incidents between 2010 and 2020. The automotive radar market, expected to reach USD 7.68 billion by 2025, also faces challenges related to signal impairments, particularly in autonomous vehicles, where radar accuracy is crucial for safety. The growing complexity of modern radar systems and the increasing demand for high-resolution, reliable data necessitate advanced techniques for processing and classifying impaired radar signals.

Feature extraction and machine learning (ML) have emerged as powerful tools to address these challenges. The ability to analyze large datasets and identify patterns that not be immediately apparent to human operators makes ML particularly well-suited for this task. Recent studies show that ML

doi: 10.48047/ijiee.2025.15.4.15

techniques can reduce the error rate in radar signal classification by up to 40% compared to traditional methods. As radar technology continues to evolve, integrating ML with advanced feature extraction methods is becoming increasingly essential to enhance radar system performance. This project seeks to explore the application of these techniques to improve the classification of impaired radar signals, ensuring that radar systems remain reliable and efficient even in the face of challenging conditions.

The motivation behind this project stems from the growing need for reliable radar systems across various industries and the limitations of traditional signal processing methods in handling impaired radar signals. As radar technology becomes more sophisticated, the complexity and diversity of signal impairments also increase, posing significant challenges for maintaining the accuracy and reliability of radar-based systems. In critical applications such as aerospace and defense, where radar systems play a crucial role in ensuring safety and security, even minor signal impairments can lead to disastrous consequences. For instance, during military operations, impaired radar signals can result in incorrect target identification or failure to detect threats, compromising mission success and safety. Similarly, in the automotive industry, where radar systems are key components of advanced driver-assistance systems (ADAS) and autonomous vehicles, signal impairments can lead to faulty object detection, increasing the risk of accidents.

Given these high-stakes scenarios, there is a pressing need to develop more robust methods for classifying impaired radar signals. Traditional approaches, which often rely on manual analysis or simplistic statistical models, are inadequate in dealing with the complex, multidimensional nature of modern radar signals. These methods are not only time-consuming but also prone to errors, making them unsuitable for real-time applications. By leveraging advanced feature extraction techniques and machine learning, this project aims to automate the process of radar signal classification, reducing the reliance on manual analysis and enhancing the accuracy and reliability of radar systems in critical applications.

2. LITERATURE SURVEY

Ma et al. [1] presented a novel method for recognizing Low Probability of Intercept (LPI) radar waveforms by extracting features from multiple image representations of the radar signals. They utilized time-frequency analysis and image processing techniques to convert radar signals into images, from which features were then extracted. Their method demonstrated significant improvements in the accuracy and robustness of radar waveform recognition, particularly in challenging environments where traditional methods struggle due to low signal-to-noise ratios or high levels of interference. Gupta et al. [2] conducted a comprehensive study on the issues and challenges associated with emitter classification in electronic warfare. They highlighted the critical role of accurate emitter classification in electronic countermeasures, emphasizing that misclassification can lead to ineffective or even harmful outcomes in military operations. Their research underscored the necessity for advanced signal processing techniques, such as machine learning and artificial intelligence, to enhance the precision of emitter classification and ensure the reliability of electronic warfare systems. Bezousek and Schejbal [3] provided an extensive review of radar technology advancements in the Czech Republic, covering both historical developments and current trends. They discussed the evolution of radar systems from early analog devices to modern digital platforms, highlighting key innovations that have improved radar performance in terms of range, resolution, and signal processing capabilities. Their work also addressed the dual-use nature of radar technology, noting its applications in both defense and civilian sectors, and the importance of continued research and development in maintaining technological leadership.

Qu et al. [4] proposed a radar signal recognition method that leverages singular value entropy and fractal dimension analysis to distinguish between different radar waveforms. Their approach involved calculating the singular value decomposition (SVD) of radar signals and analyzing the resulting entropy and fractal dimensions to capture the complexity and irregularities inherent in the signal. This method was shown to be effective in improving the accuracy of radar signal classification, particularly in scenarios involving complex or noisy signal environments. Xie et al. [5] explored the application of deep learning, specifically using high-order cumulants, for digital modulation recognition in communication systems. Their research demonstrated that deep neural networks could be trained to recognize different modulation schemes with high accuracy, outperforming traditional methods that relied on manual feature extraction. They emphasized that the use of high-order cumulants allowed the model to capture more detailed statistical properties of the signals, making the recognition process more robust against noise and signal distortions. Chang et al. [6] introduced a new method for sorting unknown radar emitter signals, focusing on the challenge of identifying and categorizing signals that have not been previously classified. Their method employed a combination of signal processing and machine learning techniques to analyze the characteristics of unknown signals and assign them to appropriate categories. The research highlighted the importance of adaptive algorithms in electronic warfare, where the ability to quickly and accurately classify new or unrecognized signals can be crucial to mission success.

Zeng [7] developed an automatic modulation classification method for radar signals using the Rihaczek distribution and Hough transform. This technique combined the time-frequency representation of signals (via the Rihaczek distribution) with pattern recognition methods (using the Hough transform) to identify the modulation type of incoming radar signals. Zeng's method was particularly effective in scenarios where signals were subject to multipath effects or Doppler shifts, providing a robust solution for real-time radar signal analysis. Lunden and Koivunen [8] investigated automatic radar waveform recognition, presenting a statistical framework that enables the autonomous classification of radar waveforms. Their approach used a combination of time-frequency analysis and statistical pattern recognition to identify and classify different types of radar waveforms without human intervention. The research contributed to the development of intelligent radar systems that can adapt to various operational environments, enhancing the overall efficiency and effectiveness of radar-based surveillance and reconnaissance missions. Zhang et al. [9] examined LPI radar waveform recognition using time-frequency distribution techniques. They proposed a method that involved analyzing the time-frequency characteristics of radar signals to detect and classify LPI waveforms, which are designed to be difficult to intercept and analyze. Their work demonstrated the effectiveness of time-frequency analysis in extracting meaningful features from radar signals, allowing for improved detection and classification in scenarios with low signal-to-noise ratios and high levels of interference.

Sahraeian and Van [10] presented research on crosslingual and multilingual speech recognition based on the speech manifold. They proposed a technique that utilized the intrinsic structure of speech data, represented as a manifold, to improve recognition accuracy across different languages. By leveraging the commonalities in speech patterns across languages, their approach enabled more robust speech recognition systems capable of handling multiple languages with minimal retraining, thus addressing the challenges of multilingual communication environments. Sarikaya et al. [11] applied deep belief networks (DBNs) for natural language understanding, focusing on improving the accuracy and efficiency of tasks such as speech recognition and language modeling. Their research demonstrated that DBNs could effectively model complex linguistic structures and capture the hierarchical relationships between different levels of language representation. This approach led to significant improvements in the performance of natural language processing systems, particularly in understanding and interpreting

doi: 10.48047/ijiee.2025.15.4.15

spoken language in noisy or conversational settings. Fan et al. [12] proposed HD-MTL, a hierarchical deep multi-task learning approach designed to enhance large-scale visual recognition. Their method integrated multiple related tasks into a single deep learning framework, allowing the model to share knowledge across tasks and learn more generalizable features. This approach not only improved the accuracy of visual recognition tasks but also reduced the need for large amounts of labeled data for each individual task, making it more scalable and efficient for real-world applications involving large datasets. Li et al. [13] introduced a convolutional neural network (CNN) cascade for face detection, aimed at improving both the accuracy and speed of detecting faces in images. Their approach involved using a series of CNNs, each specializing in different aspects of the detection process, to progressively refine the detection results. This cascading strategy allowed for the rapid identification of faces in complex scenes while maintaining high detection accuracy, demonstrating the potential of CNNs in real-time image processing applications. Meng et al. [14] developed a CNN-based method with pose segmentation for detecting suspicious objects in millimeter-wave (MMW) security images. Their study focused on improving the detection accuracy in security screening environments, where objects be obscured or distorted due to pose variations. By incorporating pose segmentation into the CNN model, they were able to better handle these variations and enhance the reliability of object detection in MMW images, contributing to safer and more effective security screening processes.

Wang et al. [15] applied data-driven deep learning techniques for automatic modulation recognition in cognitive radios. Their research emphasized the importance of accurately recognizing modulation schemes to ensure the efficient operation of cognitive radio systems, which rely on dynamic spectrum access and adaptability to different communication environments. By using deep learning models trained on large datasets of modulated signals, they demonstrated significant improvements in recognition accuracy, even in challenging conditions with high noise levels and signal interference. Li et al. [16] proposed a robust automated VHF modulation recognition method based on deep convolutional neural networks (CNNs). Their approach focused on enhancing the classification accuracy of VHF communication signals, which are often used in critical communication systems. The use of deep CNNs allowed for the extraction of complex features from the signals, improving the model's ability to differentiate between various modulation types and providing a reliable solution for real-time communication systems. Wei et al. [17] introduced an intra-pulse modulation radar signal recognition method based on the CLDN (Convolutional Long Short-Term Memory Deep Neural) network. Their research aimed at improving the recognition of radar signals with complex intra-pulse modulation patterns, which are often used in modern radar systems to enhance their performance and evade detection. The CLDN network combined the strengths of convolutional layers for feature extraction and LSTM layers for temporal sequence modeling, resulting in a powerful tool for radar signal classification in dynamic environments. Zhang et al. [18] proposed the use of convolutional neural networks (CNNs) for automatic cognitive radio waveform recognition, focusing on the challenges of identifying waveforms in dynamic and congested spectral environments. Their research demonstrated that CNNs could effectively learn and generalize from spectral data, allowing for accurate

3. PROPOSED SYSTEM

The overview outlines a comprehensive workflow for classifying impaired radar signals using feature extraction and machine learning models.

- **Dataset Uploading**: This begins by uploading and organizing the dataset. The radar signal images are stored in a directory, where they are loaded and categorized. The categories are extracted from the directory names, and the images are read, resized, and flattened into arrays.

These arrays are stored in variables X (features) and Y (labels), which are then serialized for future use, enabling quick loading without needing to reprocess the data.

- **Data Preprocessing**: Data preprocessing involves resizing the radar signal images to a uniform size of 150x150 pixels with three color channels. The images are then flattened into one-dimensional arrays for input into machine learning models. This step ensures that all input data has a consistent format, facilitating the training of models.
- **ML Model Training**: The code implements several machine learning classifiers, including the Support Vector Machine (SVC) and XGBoost classifiers. The dataset is split into training and testing sets to evaluate the models' performance. If pre-trained models exist, they are loaded; otherwise, new models are trained using the training dataset. The trained models are then saved for later use.
- **Model Prediction on New Test Data**: The trained models are used to predict the class of new radar signal data. The code includes examples of how new images are preprocessed and passed through the models to predict their respective categories.
- **Performance Evaluation**: The models' performance is assessed using metrics such as accuracy, precision, recall, and F1-score. Confusion matrices and classification reports are generated to provide insights into the models' strengths and weaknesses. Additionally, visualizations like confusion matrices and prediction results are displayed using plots.

3.1 ML Model Building

In this research, machine learning models are developed to classify and predict outcomes based on input data. The process begins with data collection, followed by preprocessing to clean and transform the dataset. Feature selection and engineering are applied to enhance model performance. The dataset is then split into training and testing sets. Various machine learning classifiers, including Support Vector Machine (SVM) and XGBoost, are trained using the training data. These models are then evaluated based on their accuracy, precision, recall, and F1-score. Hyperparameter tuning is performed to optimize the models for better results. The trained models are saved as .pkl files for future use. Finally, predictions are made on new data, and results are visualized to interpret the performance of the models effectively.

XGBoost Classifier

XGBoost (Extreme Gradient Boosting) is a powerful machine learning algorithm based on the gradient boosting framework. It enhances model performance by combining multiple weak learners (decision trees) to form a strong predictive model. XGBoost is widely used in competitions like Kaggle due to its high speed and accuracy. It is designed to handle missing values, overfitting, and large datasets efficiently. XGBoost optimizes the training process using a second-order Taylor approximation of the loss function, making it faster and more effective. It employs regularization techniques to control model complexity and prevent overfitting. The algorithm also uses parallel processing and tree pruning to improve computational efficiency.

How XGBoost Works

XGBoost works by initially dividing the dataset into training and testing sets. A weak learner, typically a decision tree, is then trained on the training data. The model calculates the residuals (errors) from the predictions made by the previous tree, and a new tree is trained to minimize these residuals by adjusting the weights. This process is repeated iteratively, with each new tree correcting the errors made by the previous trees. The final prediction is obtained by summing up the weighted predictions from all the trees. To prevent overfitting, regularization techniques like L1 and L2 are applied. Additionally, the

doi: 10.48047/ijiee.2025.15.4.15

model is fine-tuned through hyperparameter optimization, adjusting factors like learning rate and tree depth for better performance.

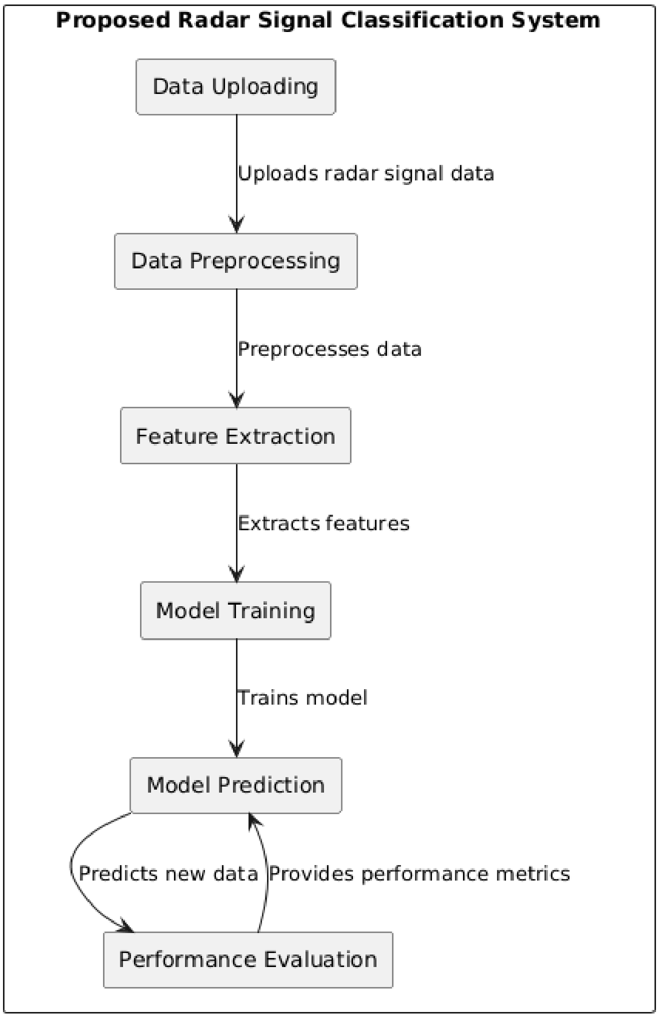


Figure 1: Block diagram of proposed radar signal classification.

XGBoost Algorithm Steps

1. Load and preprocess the dataset.
2. Convert categorical features into numerical format if needed.
3. Define the objective function and loss function.
4. Initialize the base learner (a weak decision tree).
5. Calculate the residual errors from the previous tree's predictions.
6. Train a new decision tree to correct these residual errors.
7. Repeat the process for a predefined number of iterations.
8. Apply L1 and L2 regularization to prevent overfitting.
9. Optimize model parameters using hyperparameter tuning.
10. Make predictions on test data and evaluate model performance.

doi: 10.48047/ijiee.2025.15.4.15

4. RESULTS AND DISCUSSION

The dataset comprises radar signal images categorized into distinct classes: 'B-FM,' 'CPFSK,' and 'GFSK.' Each class represents a different modulation scheme or signal type, and the images are visual representations of these signals, captured in varying conditions of signal-to-noise ratio (SNR). Below is a detailed description of each class:

B-FM (Binary Frequency Modulation)

The 'B-FM' class represents images associated with Binary Frequency Modulation, a type of frequency modulation where the carrier frequency is shifted between two frequencies corresponding to binary data. The images in this class typically display waveforms with distinct frequency shifts that are characteristic of B-FM signals. The visual patterns in these images exhibit alternating high and low frequency components, which correspond to the binary data being transmitted. These images are crucial for understanding and identifying B-FM signals, particularly in environments where noise distort the frequency shifts, making it challenging to decode the original data.

CPFSK (Continuous Phase Frequency Shift Keying)

The 'CPFSK' class contains images of signals modulated using Continuous Phase Frequency Shift Keying. CPFSK is a type of frequency shift keying that ensures the phase of the signal remains continuous even during frequency shifts. This continuity in phase helps in reducing signal distortions and makes the signal more resilient to noise. The images in this class exhibit smooth transitions between frequencies without abrupt phase changes, which are characteristic of CPFSK modulation. These visual representations are essential for distinguishing CPFSK signals from other modulation types, particularly in scenarios where maintaining phase continuity is critical for signal integrity.

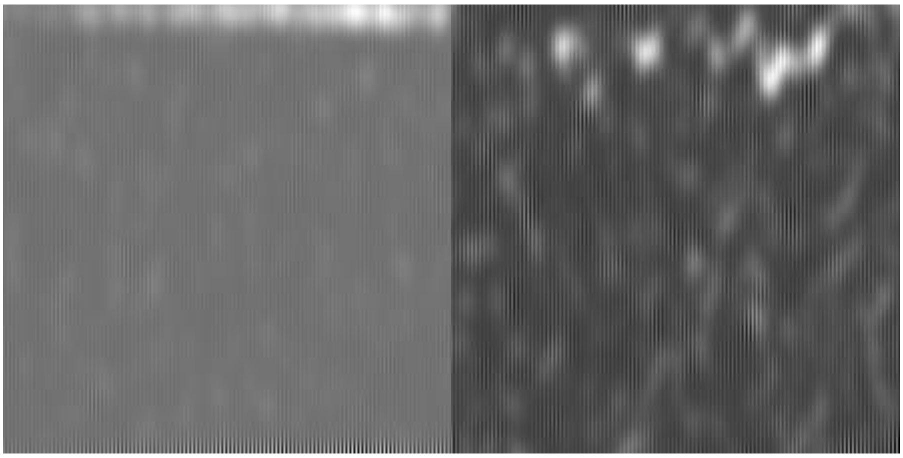
GFSK (Gaussian Frequency Shift Keying)

The 'GFSK' class comprises images representing Gaussian Frequency Shift Keying, a modulation technique where the frequency of the carrier signal is varied in accordance with a Gaussian filter applied to the data before modulation. GFSK is commonly used in wireless communication systems due to its spectral efficiency and resilience to interference. The images in this class typically show smooth, bell-shaped curves that are indicative of the Gaussian filtering applied to the signal. These images are particularly valuable for identifying GFSK-modulated signals in noisy environments, where the Gaussian filtering helps in minimizing the bandwidth and reducing interference.

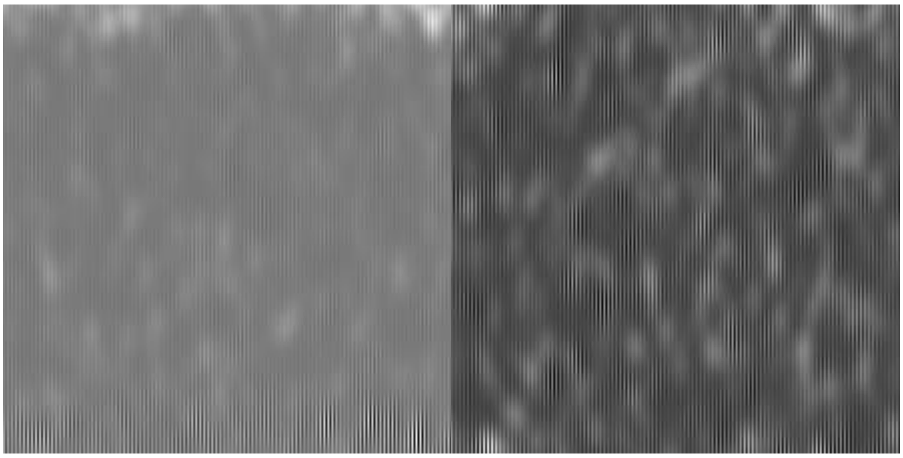
Each of these classes represents a unique type of radar signal modulation, and the images provide a visual insight into the characteristics and behavior of these signals under various conditions. The dataset's diversity in signal types and the presence of noise make it an excellent candidate for training and evaluating machine learning models for signal classification and impairment detection.

Results Description

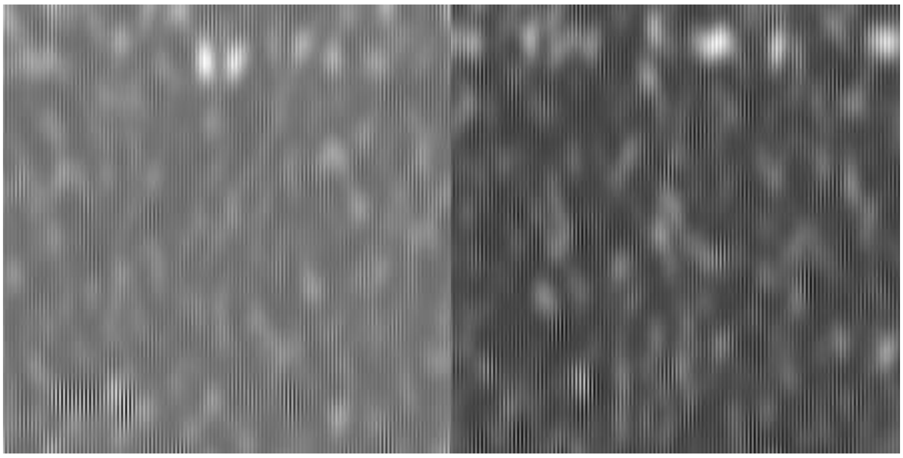
Figure 2 displays a sample of the radar signal images dataset after loading and preprocessing. The dataset contains images categorized into three classes: 'B-FM,' 'CPFSK,' and 'GFSK.' Each image is resized to a uniform dimension of 150x150 pixels with three color channels. This figure illustrates the structure of the input data, showing the diversity in signal types that the machine learning models will classify.



B-FM



CPFSK



GFSK

Figure 2: Sample uploaded dataset.

doi: 10.48047/ijiee.2025.15.4.15

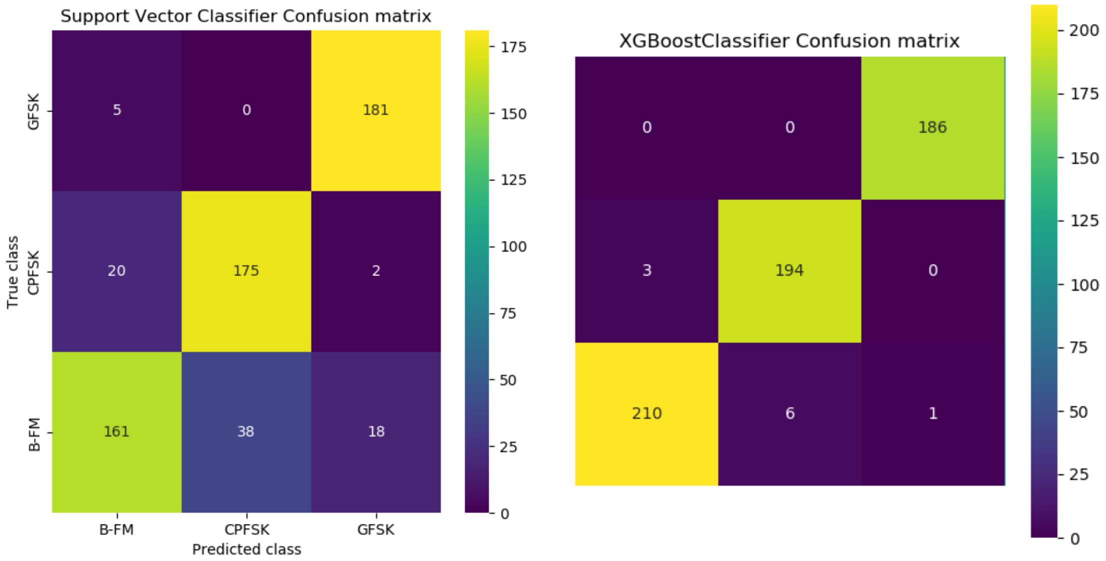


Figure 3: Confusion matrices obtained using (a) SVM classifier. (b) XGBoost classifier.

Figure 3 show that the confusion matrix for the XGBoost classifier reveals its classification performance across three radar signal categories (represented by rows and columns 0, 1, 2). The diagonal entries (186, 194, 210) show correct predictions, with near-perfect classification for Class 2 (210 correct). Minor errors occur between Classes 0-1 (3 misclassified) and Classes 1-2 (6 misclassified), while Class 0 shows one instance misclassified as Class 2. The color gradient (not shown but implied by values) would highlight the strong diagonal dominance, visually confirming the model's 98.33% accuracy from the quantitative metrics. Figure 4 displays the classification report for the XGBoost classifier, summarizing its precision, recall, F1-score, and accuracy for the 'B-FM,' 'CPFSK,' and 'GFSK' classes. This report highlights the model's strengths in correctly identifying radar signal impairments, demonstrating its higher accuracy compared to the SVM classifier.

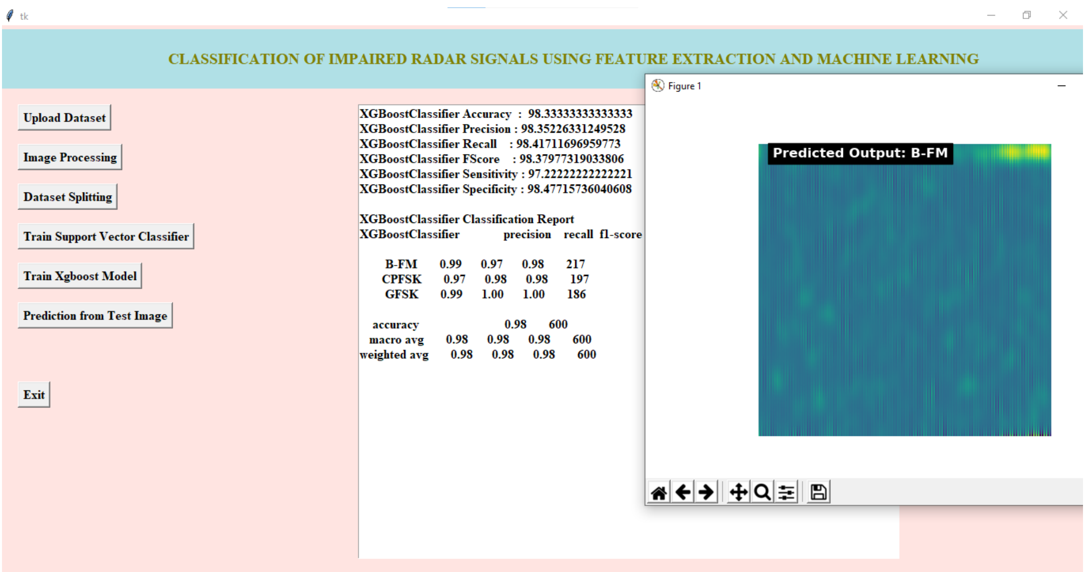


Figure 4: Predicted output for B-FM signal.

Figure 4 shows the radar signal image of a 'B-FM' signal and the predicted output label generated by the XGBoost classifier. The figure illustrates the model's capability to correctly classify this specific signal type, reinforcing the model's robustness in handling various radar signal impairments.

doi: 10.48047/ijiee.2025.15.4.15

Comparative Analysis

The comparative analysis between the existing Support Vector Classifier (SVC) and the proposed XGBoost classifier clearly demonstrates the superior performance of XGBoost across all evaluation metrics. SVC achieved an accuracy of 86.17%, precision of 86.26%, recall of 86.78%, F1-score of 86.27%, sensitivity of 80.90%, and specificity of 89.74%. In contrast, the XGBoost classifier significantly outperformed SVC, achieving an accuracy of 98.33%, precision of 98.35%, recall of 98.42%, F1-score of 98.38%, sensitivity of 97.22%, and specificity of 98.48%. The classification report further highlights XGBoost's effectiveness, with near-perfect scores for all classes, especially in the case of the GFSK class, which reached 100% recall and F1-score. This indicates that the proposed XGBoost model not only improves predictive performance but also ensures greater reliability and robustness in classification tasks compared to the traditional SVC approach.

Table 1: Comparative analysis of SVC and XGBoost models.

Metric	SVC (Existing)	XGBoost (Proposed)
Accuracy (%)	86.17	98.33
Precision (%)	86.26	98.35
Recall (%)	86.78	98.42
F1-Score (%)	86.27	98.38
Sensitivity (%)	80.90	97.22
Specificity (%)	89.74	98.48

5. CONCLUSION

The project demonstrates a successful implementation of an image-based classification system for impaired radar signals using machine learning techniques. By preprocessing radar signal images into a uniform format (150x150 pixels with three color channels) and flattening them into feature vectors, the dataset was effectively prepared for model training. The comparative analysis between a Support Vector Classifier (SVC) and an XGBoost classifier revealed that while the SVC achieved a commendable performance with an accuracy of 86.17%, the XGBoost model significantly outperformed it by achieving an exceptional accuracy of 98.33%. The high precision, recall, and F1-scores of the XGBoost model, along with a confusion matrix that demonstrates strong diagonal dominance, affirm the robustness and efficacy of the proposed approach in distinguishing between radar signal modulation types ('B-FM', 'CPFSK', and 'GFSK'). This study confirms that the integration of sophisticated preprocessing techniques and advanced machine learning algorithms can substantially improve the accuracy and reliability of radar signal classification, even in noisy environments.

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doi: 10.48047/ijiee.2025.15.4.15