

Detection of Bearing Faults from Vibration Signals

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Abstract— Bearings are critical mechanical components in rotating machinery, playing a vital role in system safety and operational continuity. In this study, the Case Western Reserve University (CWRU) bearing dataset is used to perform fault classification using four machine learning algorithms: Random Forest, XGBoost, Support Vector Machine (SVM), and Naive Bayes. Based on statistical features extracted in the time domain, the performance of each model is evaluated using accuracy, precision, recall, and F1-score metrics. The results reveal that Random Forest and XGBoost algorithms achieved superior performance with 95.73% accuracy and 96% in precision, recall, and F1-score. The SVM model, with 93.73% accuracy, stands out as a robust alternative, while the Naive Bayes algorithm shows relatively lower performance with 92.40% accuracy. Additionally, an individual feature-based classification analysis indicates that standard deviation (sd) and root mean square (RMS) features contribute most significantly to model performance. This study provides a comprehensive performance analysis of traditional machine learning algorithms, offering a valuable reference for early and accurate detection of bearing faults.

Index Terms— Bearing fault diagnosis, Machine learning, Random Forest, XGBoost, Support Vector Machine, Naive Bayes, CWRU dataset.

I. INTRODUCTION

BEARINGS are among the most fundamental and mission-critical components in rotating machinery, playing a pivotal role in ensuring mechanical performance, operational reliability, and safety.

Structurally, a typical bearing comprises an inner race, an outer race, rolling elements (usually balls or rollers) positioned between these races, and a cage that maintains the spacing and alignment of the rolling elements. This configuration enables the bearing to accommodate both radial and axial loads while minimizing friction, thereby contributing significantly to the energy efficiency of mechanical systems. Bearings are ubiquitous in various industrial domains, including aerospace, automotive, wind energy, railway transportation, industrial drives, and automated production systems. In such applications, they are often subjected to harsh operational environments characterized by variable loads, elevated temperatures, and persistent vibrations. These demanding conditions, over

extended periods, give rise to a variety of structural degradations such as surface fatigue, micro-cracking, plastic deformation, pitting, and spalling. If left undetected, such defects can evolve rapidly and pose serious risks to the mechanical integrity and safety of the overall system. Empirical studies report that nearly 40% of failures in rotating machinery can be attributed to bearing faults. Despite their relatively low cost compared to other mechanical subsystems, bearings possess a strategically critical function. A single bearing malfunction has the potential to cause collateral damage to adjoining components such as shafts, gear trains, and motor assemblies, often resulting in costly production downtimes and substantial financial losses. Given these risks, real-time monitoring and early fault detection in bearings are indispensable for preventing unplanned outages and optimizing maintenance scheduling. Timely diagnosis of incipient faults not only mitigates the likelihood of catastrophic equipment failure but also reduces maintenance expenditures, enhances operational efficiency, and improves the overall reliability of the system [1-3].

Over time, bearings undergo deterioration as a result of prolonged exposure to adverse operating conditions, including excessive mechanical loads, irregular torque fluctuations, inadequate lubrication, and environmental contaminants such as dust and moisture. Additionally, sudden mechanical shocks can accelerate this degradation process. Among the most prevalent types of bearing failures are defects in the inner race, cracks in the outer race, surface wear or pitting on rolling elements, and deformation of the cage. As these faults evolve, they lead to increased vibrational and acoustic emissions, reduced mechanical efficiency, and compromised system stability. Ultimately, undetected or untreated bearing damage can culminate in critical equipment failures, unplanned production interruptions, and considerable economic consequences [4].

Rotating machinery is extensively utilized across a range of industrial domains, including aerospace, automotive, energy production, and transportation systems. Within these machines, rolling bearings serve as crucial mechanical elements due to their role in ensuring smooth and reliable operation. Studies have revealed that nearly 40% of mechanical malfunctions stem from bearing-related faults, a figure that may escalate to 90% in smaller-scale equipment. Such malfunctions can pose serious safety hazards, disrupt operations, and lead to substantial financial repercussions. Consequently, there is an increasing demand for reliable and automated bearing fault diagnosis systems. In this context, machine learning approaches have emerged as powerful

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tools for fault detection, isolation, and classification, offering the advantage of minimizing reliance on domain-specific expertise or manual supervision. Traditional techniques such as artificial neural networks (ANN), support vector machines (SVM), k-nearest neighbors (k-NN), and principal component analysis (PCA) have been widely adopted in this domain. However, these methods often involve distinct steps for feature extraction and classification, where informative features must be manually derived from raw sensor signals. Moreover, their performance tends to decline when faced with large-scale or complex datasets, indicating limited scalability and generalization capacity. In light of these challenges, deep learning methodologies have garnered attention for their capability to autonomously learn discriminative representations from high-dimensional data while simultaneously performing classification tasks [5].

Rotating machinery is extensively utilized in modern industrial applications such as compressors, pumps, conveyor systems, and electric motors. Among the essential components in these machines, rolling bearings are pivotal in maintaining the system's reliability and operational integrity. Nevertheless, prolonged operational durations and exposure to severe environmental conditions render these components susceptible to degradation and eventual failure. As such, the development of advanced diagnostic methodologies for the early detection of bearing faults is vital to ensure equipment reliability, mitigate unplanned downtimes, and minimize economic losses. A variety of sensing techniques have been implemented in recent years for condition monitoring and fault diagnosis of rolling bearings. These include, but are not limited to, vibration analysis, acoustic emission detection, sound signature analysis, thermal imaging, and motor current signal analysis. Of these, vibration analysis remains the most prevalent and effective diagnostic approach due to its sensitivity to mechanical anomalies. It is particularly effective in identifying four principal fault categories: defects in the outer race, inner race, rolling elements, and cage structures. The presence of a fault typically induces repetitive transient pulses within the vibration signal, providing diagnostic cues for fault detection and classification [6].

Contemporary industrial machinery frequently operates in dynamic and often harsh environments, characterized by structural complexity and variable load conditions. These factors elevate the risk of minor defects escalating into systemic failures, thereby compromising equipment reliability and posing potential safety hazards. To mitigate such risks, accurate estimation of the remaining useful life (RUL) and reliable fault diagnosis of critical components—such as bearings—are essential. The recent progress in machine learning has facilitated the development of advanced diagnostic frameworks capable of achieving high accuracy in fault identification. In contrast to conventional methods, intelligent fault diagnosis systems offer automated feature extraction and integrated classification capabilities, reducing dependency on manual preprocessing. The effectiveness of these systems is influenced not only by the

robustness of the algorithmic models but also by the quality and structure of the datasets employed. Despite widespread reliance on balanced datasets in experimental studies, this assumption rarely holds true in industrial environments, where data imbalance is a common issue—particularly due to the scarcity of fault-related data compared to normal operating conditions [7].

Conventional approaches to bearing fault detection predominantly rely on time-frequency domain analyses and handcrafted feature extraction. Methods such as Fast Fourier Transform (FFT), Wavelet Transform (WT), and Empirical Mode Decomposition (EMD) have been widely utilized for signal interpretation in diagnostic applications. While these techniques have demonstrated effectiveness in controlled scenarios, they often exhibit sensitivity to noise and require significant expert knowledge for parameter tuning and feature design. Such dependencies restrict their applicability in complex, real-world environments and hinder automation. As a result, there has been a paradigm shift toward data-driven techniques, particularly those based on machine learning (ML) and deep learning (DL), which offer more robust and scalable solutions by enabling end-to-end learning directly from raw or minimally processed sensor data [4].

Timely identification of bearing faults is essential to enhance system reliability and reduce operational maintenance expenses. Conventional diagnostic techniques primarily utilize signal processing approaches in the time, frequency, and time-frequency domains. Commonly applied methods include wavelet transform, short-time Fourier transform (STFT), empirical mode decomposition (EMD), variational mode decomposition (VMD), and continuous wavelet transform (CWT), which aim to reveal hidden fault characteristics within vibration signals. Despite their widespread use, these methods are often constrained by their dependency on manually selected parameters and prior domain expertise, which can limit adaptability and reduce performance under varying operating conditions [8,9].

In recent years, to address the limitations of conventional approaches, the adoption of machine learning and deep learning techniques in bearing fault diagnosis has gained significant momentum. While classical machine learning algorithms such as support vector machines (SVM), decision trees (DT), k-nearest neighbors (k-NN), and random forests (RF) continue to be utilized, more sophisticated deep learning architectures have demonstrated remarkable performance. These include convolutional neural networks (CNN), long short-term memory networks (LSTM), spiking neural networks (SNN), autoencoders, generative adversarial networks (GAN), and transformer-based models. Their ability to autonomously extract hierarchical features from raw data and adapt to complex fault patterns makes them powerful tools in modern fault diagnosis systems [10,11].

In conclusion, bearing fault diagnosis is of critical importance in modern industry. Studies conducted using the CWRU dataset have shown that machine learning and deep learning methods can be effectively applied in this domain. In this context, the present study utilizes the CWRU dataset

to extract time-domain features and comparatively analyze the classification performance of different machine learning algorithms (RF, SVM, XGBoost, NB).

II. LITERATURE REVIEW

In this section, the literature on bearing fault diagnosis is summarized.

Li et al. (2024) developed a novel deep learning framework to improve the accuracy of fault identification in essential mechanical systems. Addressing the deficiencies of conventional methods in extracting fault-related information from rotating machinery, the study introduced an attention-augmented Convolutional Neural Network (CNN) architecture, termed Attention Improved CNN (AT-ICNN). This architecture combines an enhanced convolutional module (IMConv) with a hybrid attention mechanism, allowing for the effective extraction of both local and global signal characteristics and emphasizing critical fault features. Consequently, the proposed model demonstrates superior fault classification capabilities. The AT-ICNN was validated on the widely-used Case Western Reserve University (CWRU) bearing dataset and an in-house laboratory dataset. It achieved classification accuracies of 98.12% and 98.72%, respectively, surpassing traditional and state-of-the-art methods by nearly 9%. These outcomes highlight the model's potential as a reliable and high-performance solution for fault diagnosis in industrial mechanical components [12].

Borghesani et al. (2023) sought to advance the transparent and theoretically grounded development of neural networks (NNs) specifically within the domain of Machine Condition Monitoring (MCM). They highlighted the structural parallels between NN layers and classical signal processing operations—such as filtering, decimation, and envelope extraction—and conducted a rigorous mathematical analysis of these similarities. Given that MCM frequently deals with signals characterized by periodic and cyclostationary behavior, the authors employed a Fourier-based framework to elucidate the influence of NN layers on such signal types. This analysis provided a foundation for establishing design heuristics and parameter optimization strategies tailored to MCM tasks, drawing upon long-standing insights from signal processing literature. The research aligns with contemporary movements in Explainable Artificial Intelligence (XAI) and Physics-Informed Neural Networks (PINNs), aiming to rationalize parameter choices without deviating from standard NN structures. The proposed methodology was substantiated via numerical simulations and experimental validation on the Case Western Reserve University (CWRU) bearing dataset. Overall, the study delivers a structured and interpretable framework for constructing neural networks optimized for MCM contexts [13].

Xu et al. (2021) introduced a hybrid deep learning framework designed to improve the accuracy of bearing fault diagnosis, which is vital for minimizing economic losses in industrial environments. Recognizing that many conventional deep learning models, such as CNN and

gcForest, tend to underemphasize the feature extraction stage, the authors integrated these two architectures into a complementary hybrid model. In their approach, vibration signals from bearings were first converted into time-frequency representations via Continuous Wavelet Transform (CWT). These transformed images served as inputs to a Convolutional Neural Network (CNN), which extracted discriminative features related to fault characteristics. The extracted features were then input into a gcForest classifier for final classification. The model was validated using bearing fault datasets from both Case Western Reserve University (CWRU) and Xi'an Jiaotong University (XJTU-SY). Comparative experiments demonstrated that the CNN + gcForest combination significantly outperformed the individual models, offering superior fault detection accuracy. These findings underscore the model's potential applicability in real-world diagnostic systems by enhancing robustness and classification precision [14].

Similarly, Li (2024) introduced a novel deep learning architecture named DPW ATTCNN, specifically designed to facilitate fast and precise bearing fault diagnosis in a cost-effective and deployment-friendly manner. To minimize computational complexity, the model utilizes Depthwise Separable Convolution (DPW), which significantly reduces the number of trainable parameters without compromising feature extraction capabilities. Additionally, the incorporation of an Efficient Channel Attention (ECA) mechanism enables the model to capture and emphasize critical inter-channel dependencies, thereby improving its representational power. To enhance the model's performance across varying operational environments, Adaptive Batch Normalization (AdaBN) was employed, allowing effective domain adaptation. The model's performance was rigorously evaluated on the Case Western Reserve University (CWRU) bearing dataset, achieving an impressive classification accuracy of 99.58%. Even under high levels of additive noise, the model preserved over 95% accuracy, and domain transfer experiments yielded an average recognition rate of 97.35%. These results affirm DPW ATTCNN's high robustness and its capacity for generalization in real-world fault diagnosis scenarios [15].

Wu et al. (2024) presented a comprehensive approach to overcome two critical challenges in bearing fault diagnosis under varying operational environments: class imbalance and domain distribution divergence. These factors are known to degrade model generalization and often result in poor recognition of minority fault categories, thereby limiting diagnostic reliability. To address this, the authors developed a novel framework called Iterative Resampling Deep Decoupling Domain Adaptation (IRDDDA). The IRDDDA architecture integrates four key modules: a feature extractor, a domain discriminator, a label predictor, and a feature resampler, operating within a decoupled two-phase training paradigm. During the initial phase, domain-invariant representations are learned from imbalanced datasets across source and target domains. In the subsequent phase, a feature-wise resampling strategy is employed to alleviate

classification bias caused by class imbalance, while the upper layers of the feature extractor are iteratively refined to enhance model performance. The efficacy of the model was assessed using both the publicly available Case Western Reserve University (CWRU) dataset and experimental data acquired from the authors' custom-built bearing test platform. Empirical results demonstrated that IRDDDA consistently achieved higher and more balanced classification accuracy, particularly for underrepresented fault classes, and delivered robust generalization across domains. The study underscores the advantage of jointly addressing data imbalance and domain discrepancy in the development of reliable fault diagnosis systems [16].

Gu et al. (2022) introduced a novel hybrid methodology aimed at enhancing the precision of fault diagnosis in rolling bearings, which serve as essential components in mechanical manufacturing and transport systems. The primary objective was to effectively identify fault-related features from weak and noise-contaminated signals, particularly in cases involving small-sized datasets. The proposed method integrates multiple advanced techniques, including Variational Mode Decomposition (VMD), Continuous Wavelet Transform (CWT), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM). Initially, vibration signals are preprocessed and decomposed into several Intrinsic Mode Functions (IMFs) via VMD. These IMFs are then converted into two-dimensional time-frequency representations using CWT. A CNN model, designed with carefully optimized hyperparameters, is employed to learn discriminative features from these images. Unlike conventional approaches that rely on Softmax layers for classification, this framework utilizes an SVM classifier in the final stage to improve robustness and accuracy. The proposed strategy was validated using both the Case Western Reserve University (CWRU) bearing dataset and a spindle fault dataset acquired from a dedicated test bench. Experimental evaluations revealed that the method achieved an average accuracy of 99.9% on the CWRU dataset and 90.15% on the spindle fault dataset. These results demonstrate the superior performance of the hybrid model over traditional CNN-based and feature engineering-based methods, confirming its potential in terms of diagnostic precision and generalization capacity across different fault scenarios [17].

Huang and Zhao (2024) presented an innovative deep learning architecture designed to enhance both the accuracy and efficiency of bearing fault diagnosis, with particular emphasis on the early identification of weak fault signals—an essential requirement for ensuring the dependable operation of rotating machinery. Their proposed method integrates three fundamental components. Firstly, an Improved Multi-Scale Feature Fusion Residual Network (IMSFFRN) is developed, which utilizes convolutional layers with diverse dilation rates to extract features at multiple scales. This configuration facilitates the effective fusion of intermediate representations, thereby enabling the model to capture more detailed and hierarchical characteristics from vibration signals. Secondly, acknowledging that different diagnostic features contribute

unevenly to fault classification, the authors incorporated a Multiple-Winning Consciousness Self-Organizing Map (MCSOM) competitive mechanism. This layer enhances the discriminative capability of individual neurons by learning their sensitivity to particular fault types. Thirdly, to strengthen the model's generalization ability, a Support Vector Machine (SVM) is employed during the classification phase. The performance of the proposed framework was rigorously evaluated on three benchmark datasets: CWRU, PU, and SEU, where it achieved exceptional classification accuracies of 100%, 99.56%, and 100%, respectively—surpassing several state-of-the-art approaches. Furthermore, the model maintained high classification reliability under noisy conditions, highlighting its robustness. These findings confirm that the multi-scale competitive architecture is particularly suitable for early-stage fault detection in real-world industrial environments where signal degradation and noise are prevalent [18].

Zhang et al. (2024) proposed a robust and noise-resilient approach to tackle the significant challenges of condition monitoring and fault diagnosis of rolling bearings—key components in mechanical systems—under high-noise environments commonly encountered in industrial settings. Recognizing that traditional diagnostic models often struggle with the degradation of signal quality due to noise, the authors introduced a novel framework named Stochastic Resonance-assisted Deep Neural Network (SRDN). This method embeds the Stochastic Resonance (SR) mechanism within a Spiking Neural Network (SNN) architecture to amplify weak and noisy fault signals. By leveraging the SR effect, the model enhances the signal-to-noise ratio (SNR) of input signals before classification, enabling more accurate recognition of subtle fault characteristics. The SRDN model was tested on the widely used Case Western Reserve University (CWRU) bearing dataset, achieving an outstanding classification accuracy of 99.9%. More notably, even under severe noise conditions such as -8 dB SNR, the model sustained an accuracy exceeding 92%, indicating exceptional robustness and generalization. These results suggest that integrating SR mechanisms into neural network architectures significantly improves diagnostic performance in noisy environments and demonstrates high potential for deployment in real-world fault diagnosis systems where signal clarity cannot be guaranteed [19].

Han and Jeong (2020) highlighted the broader implications of bearing fault diagnosis, noting its influence not only on mechanical reliability but also on production efficiency and operational strategy. Their study sought to improve the practical applicability and robustness of deep learning models by simulating more realistic industrial conditions. While deep learning methods reported in the literature often achieve high diagnostic accuracy, these outcomes are typically derived from idealized, noise-free datasets collected in controlled simulator environments—conditions that rarely mirror actual factory settings. To bridge this gap, the authors augmented the widely used Case Western Reserve University (CWRU) bearing dataset with Gaussian noise to emulate the signal distortions commonly

found in industrial environments. They then proposed a Weighted Arithmetic Mean CNN Ensemble Model, which demonstrated enhanced classification performance compared to both standard CNN and unweighted ensemble models. Evaluation metrics, including accuracy and F1-score, confirmed the ensemble model's superiority in handling noisy and limited data. These results underscore the importance of robust ensemble strategies for industrial deployment, and suggest that the proposed method offers a practical and reliable solution for real-world fault diagnosis applications under non-ideal conditions [20].

Chen et al. (2023) addressed a critical challenge in intelligent fault diagnosis: the mismatch of data distributions resulting from varying operating conditions, which significantly hinders the performance of diagnostic models in real-world industrial settings. While conventional transfer learning techniques offer partial solutions to this issue, they often neglect the seamless integration of low-dimensional pre-learned features with high-dimensional deep representations, limiting their effectiveness. To resolve this limitation, the authors introduced a residual convolutional transfer learning framework guided by slow-varying features. Initially, Slow Feature Analysis (SFA) was utilized to extract latent representations that encapsulate the intrinsic and stable characteristics of the mechanical system. These features were then passed through a Residual Convolutional Network to learn deeper abstract representations. A bypass mechanism was employed to fuse low- and high-level features, ensuring comprehensive feature integration. Moreover, to mitigate domain discrepancies between the source and target data, the Maximum Mean Discrepancy (MMD) metric was applied in the Reproducing Kernel Hilbert Space (RKHS) to align distributions effectively. The framework was validated using the Xi'an Jiaotong University (XJTU) and Case Western Reserve University (CWRU) bearing datasets. Experimental outcomes demonstrated that the proposed method achieved over 99% classification accuracy across both datasets, confirming its strong transfer learning capability and resilience under dynamic operational environments. These findings highlight the framework's potential for deployment in industrial fault diagnosis applications involving significant domain shifts [21].

Gupta et al. (2024) introduced an innovative diagnostic approach termed the Discriminant Analysis-based Unimodality Test (DAT), aimed at enhancing the classification of time series data into unimodal or multimodal categories. Beyond this primary objective, DAT is also capable of detecting anomalies, estimating key statistical parameters, and identifying data skewness. The method is particularly effective in binary classification scenarios and demonstrates robust performance across both unimodal and multimodal datasets. In comparative analyses with established unimodality tests—specifically the dip test and the folding test—DAT consistently delivered superior accuracy and stability. To further validate its applicability, the authors extended DAT's functionality to fault detection tasks by evaluating its performance on the Case Western Reserve University (CWRU) bearing dataset. Five different

machine learning classifiers were employed in this validation, and the method demonstrated exceptional diagnostic precision, successfully detecting bearing faults as small as 0.007 inches with a remarkable 99.999% accuracy. These results underscore DAT's potential as a powerful tool for industrial anomaly detection, offering significant improvements over traditional techniques, particularly in scenarios where high sensitivity to subtle fault signatures is required [22].

Hou et al. (2023) introduced a novel deep learning framework, named Diagnosisformer, which leverages a multi-feature parallel fusion strategy embedded within a Transformer-based architecture to improve the performance of bearing fault diagnosis. Aiming to overcome the limitations of conventional deep learning models—particularly their low diagnostic accuracy and limited robustness—the proposed model employs a structured approach for enhanced feature representation. Initially, Fast Fourier Transform (FFT) is used to extract frequency-domain features from raw vibration signals, followed by normalization and embedding steps. These processed features are then input into a parallel fusion encoder capable of simultaneously capturing both local and global signal characteristics. The resulting feature representations are passed through a cross-flipped decoder before reaching the classification module. The Diagnosisformer model was validated using two datasets: one collected from a laboratory-scale rotating machinery test rig and the publicly available Case Western Reserve University (CWRU) bearing dataset. The model achieved average classification accuracies of 99.84% and 99.85% on the respective datasets, surpassing benchmark methods. These findings affirm the model's superior diagnostic accuracy, generalization ability, and robustness under noisy conditions. The study ultimately highlights the potential of attention-based Transformer architectures as a robust and efficient solution for intelligent fault detection in industrial settings [23].

III. CWRU DATASET

The Case Western Reserve University (CWRU) bearing dataset has become a benchmark resource in the field of machine condition monitoring and predictive maintenance research. Its structured composition, high-fidelity vibration measurements captured under well-controlled experimental conditions, and detailed categorization of fault types and severities make it a widely adopted dataset for evaluating diagnostic algorithms. The dataset was generated using a custom-designed bearing fault test rig located in the Electrical Engineering Laboratory at Case Western Reserve University. As shown in Figure 3.1, the experimental system consists of a 2-hp induction motor, a torque transducer, a dynamometer, and two accelerometers strategically placed at the motor's drive end and fan end. Vibration data were typically recorded at high sampling rates of 12 kHz and 48 kHz, allowing for fine-resolution signal analysis suitable for fault detection tasks [24].

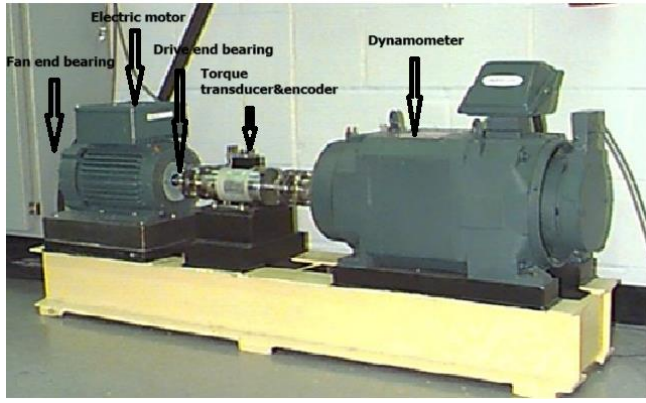


Figure 3. 1 CWRU Bearing Test Rig Experimental Platform

The bearing defects in the CWRU dataset were intentionally induced using the Electro-Discharge Machining (EDM) technique to simulate real-world fault scenarios in a controlled environment. These defects are systematically categorized into four primary classes: Normal (No Fault), Inner Race Faults, Outer Race Faults, and Ball (Rolling Element) Faults. To examine the effects of fault severity on diagnostic accuracy, each fault category was fabricated in three distinct sizes, corresponding to diameters of 0.007 inches, 0.014 inches, and 0.021 inches. This gradation of defect sizes enables comprehensive analysis of model sensitivity to varying levels of damage [25].

As shown in Figure 3.2, there are significant differences in vibration amplitude and waveform between the healthy condition and various fault types in the dataset (e.g., inner race, outer race, and rolling element faults). For instance, the ball fault in file *B021_1_227* is characterized by more irregular and abrupt amplitude changes over time; meanwhile, in *IR021_1_214*, the inner race fault presents with prominent vibration peaks. On the other hand, the *OR021_6_1_239* outer race fault scenario exhibits more periodic fault-induced impacts in the signal. In contrast, the healthy condition signal in *Time_Normal_1_098* displays a low-amplitude and more stable pattern.

The CWRU bearing dataset encompasses a total of 161 individual datasets, systematically grouped according to fault location and signal sampling frequency. These groups include normal (healthy) condition, 12kHz drive-end fault, 48kHz drive-end fault, and 12kHz fan-end fault scenarios. Each category contains three primary fault types: inner race faults (IF), ball (rolling element) faults (BF), and outer race faults (OF). Vibration signals were acquired under varying operational conditions, with motor speeds ranging from 1720 to 1797 revolutions per minute (RPM) and at load levels of 0, 1, 2, and 3 horsepower (HP). Furthermore, measurements were taken from multiple sensor placements on the experimental platform, including Centered (6:00 orientation), Orthogonal (3:00 orientation), and Opposite (12:00 orientation) positions, providing diverse perspectives of fault-induced signal characteristics [26].

The CWRU dataset is widely used for benchmarking the accuracy of machine learning and deep learning models.

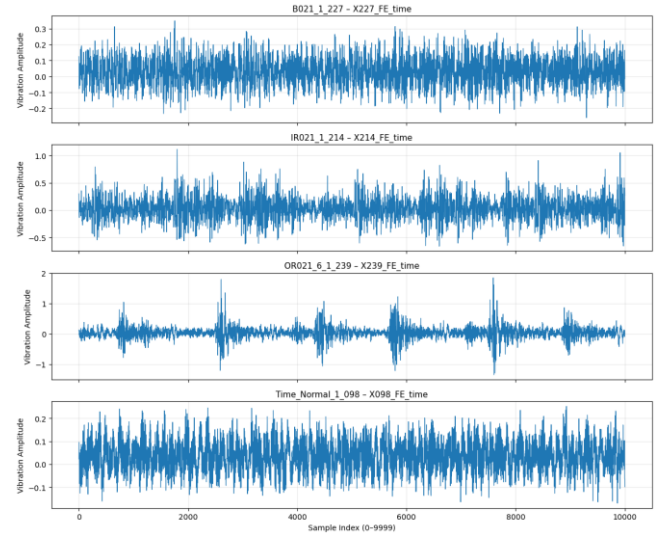


Figure 3. 2 Some example time-domain vibration signals from the CWRU bearing dataset.

Due to its high sampling rate and diversity in motor loads and fault sizes, it enables the development of classification, transfer learning, data augmentation, signal processing, and predictive maintenance algorithms. As one of the most cited open datasets in the field of predictive maintenance, the CWRU bearing dataset holds significant importance in both academic and practical research. It serves as a fundamental resource for deep learning-based bearing fault diagnosis studies, both at the initial stage and for advanced model comparisons.

IV. METHOD

A. SUPPORT VECTOR MACHINES (SVM)

Support Vector Machines (SVM) are a supervised learning-based, powerful classification method with high generalization capability. The main objective of SVM is to define an optimal hyperplane that separates examples belonging to different classes with the maximum margin. This method operates on a training dataset $D = \{(x_i, y_i)\}_{i=1}^N$ where $x_i \in R^n$ as input vectors and $y_i \in \{-1, +1\}$ as class labels. In linearly separable datasets, this hyperplane is represented by the following decision function:

$$f(x) = \langle w, x \rangle + b \quad (1)$$

Here, w is the normal vector to the hyperplane, and b is the bias term. To maximize the margin width, SVM solves the following optimization problem:

$$\min_{w, b} \frac{1}{2} \|w\|^2 \quad \text{subject to } y_i (w^T x_i + b) \geq 1, \quad \forall i \quad (2)$$

Since real-world data are often not linearly separable, the model is converted into a soft-margin form. In this case, slack variables ξ_i that allow for classification errors and a regularization parameter C are introduced, leading to the following optimization formulation:

$$\min_{w,b,\xi} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \xi_i \quad \text{subject to} \\ y_i(w^T x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0 \quad (3)$$

The hyperparameter C provides a balance between model complexity and classification errors. Smaller values of C allow for a wider margin, while larger values aim to reduce classification errors.

A significant advantage of SVM is its capacity to solve non-linear classification problems. For this purpose, input data are transformed into a higher-dimensional feature space using kernel functions, making them linearly separable in that space. The kernel function enables the measurement of similarity without explicitly computing the transformation ϕ . One of the most widely used kernel functions is the Radial Basis Function (RBF) kernel, defined as:

$$K(x_i, y_i) = \exp\left(-\gamma \|x_i - x_j\|^2\right), \quad \gamma = \frac{1}{2\sigma^2} \quad (4)$$

This kernel function is particularly well-suited for modeling non-linear patterns. During training, only the data points closest to the margin—called support vectors—determine the decision boundary. As a result, SVM offers a sparse model structure that is resistant to overfitting, even in high-dimensional datasets [27,28].

B. RANDOM FOREST (RF) METHOD

Random Forest (RF) is one of the ensemble learning algorithms developed by Leo Breiman, consisting of a combination of multiple decision trees. This method, which can be applied to both classification and regression problems, aims to reduce the bias of individual decision trees and enhance the model's generalization ability by training multiple trees independently and aggregating their results. The fundamental working principle of the RF algorithm is to construct each tree using bootstrap sampling of the training dataset and to perform node splitting based on a randomly selected subset of features. These strategies reduce the correlation between trees and significantly lower the risk of overfitting by increasing the diversity within the ensemble. For classification problems, the RF algorithm performs majority voting based on the predictions obtained from each decision tree. Mathematically, this process is carried out over T decision tree classifiers such as $h_1(x), h_2(x), \dots, h_T(x)$,

$$\hat{y} = \text{mod } e\{h_1(x), h_2(x), \dots, h_T(x)\} \quad (5)$$

It is expressed as such, where xxx represents the input vector, and the output of the RF model is represented by the result of the voting process. There are two main hyperparameters that significantly influence the performance of the RF algorithm:

- **n_estimators (T):** The number of trees in the forest. Increasing the number of trees generally results in more

stable outcomes, but also increases computational cost.

- **max_features (m):** The number of features considered when splitting a node. This parameter helps reduce correlation between trees and improves the generalization capability of the model.

During the construction of each decision tree, impurity measures such as Gini impurity or entropy are commonly used for node splitting. The Gini impurity is calculated as follows:

$$Gini(D) = 1 - \sum_{i=1}^C p_i^2 \quad (6)$$

Here, D denotes the dataset at a given node, C represents the number of classes, and P_i is the proportion of samples belonging to the i^{th} class. The entropy criterion is defined as:

$$Entropy(D) = - \sum_{i=1}^C p_i \log_2(p_i) \quad (7)$$

The RF algorithm stands out with its robustness against overfitting, effective performance on high-dimensional datasets, and ability to handle missing data. Moreover, it provides interpretability through feature importance rankings. Thanks to these advantages, RF is widely used in both classification and regression tasks. In recent years, RF-based approaches have demonstrated successful results in various application domains such as financial modeling, environmental systems, and subsurface resource classification, as highlighted in the literature [29,30].

C. NAIVE BAYES (NB) ALGORITHM

The Naive Bayes (NB) algorithm is a supervised classification method based on probability theory and rooted in Bayes' Theorem. The core assumption of this method is that all features used in classification are conditionally independent of each other. This assumption increases the simplicity of the model and reduces computational time; however, in some cases, it may also affect classification accuracy.

The Naive Bayes algorithm, for each class, relies on Bayes' Theorem to determine to which class the observed features belong when a feature vector $X = (x_1, x_2, \dots, x_n)$ is given:

$$P(C_k | X) = \frac{P(X | C_k) \cdot P(C_k)}{P(X)} \quad (8)$$

Here:

$P(C_k | X)$: It is the posterior probability of class C_k given the observation set X .

$P(X | C_k)$: It is the likelihood of observing X given class C_k .

$P(C_k)$: It is the prior probability of class C_k .

$P(X)$: It is the marginal probability of the observed X .

Naive Bayes is called “naive” because it assumes that the features are conditionally independent of each other. Thanks

to this assumption, the conditional probability can be decomposed as follows:

$$P(X \setminus C_k) = \prod_{i=1}^n P(X_i \setminus C_k) \quad (9)$$

In this case, the classification decision is made by selecting the class with the highest probability, as shown below:

$$\hat{C} = \arg \max_{C_k} P(C_k) \cdot \prod_{i=1}^n P(X_i \setminus C_k) \quad (10)$$

The Naive Bayes (NB) algorithm offers several advantages, including short training time, high accuracy on small-sized datasets, and the ability to perform well even in high-dimensional feature spaces. Among its strengths are computational simplicity, fast model training, and low memory usage. However, its most significant drawback is the assumption of feature independence, which is not always realistic. As a result, the classification accuracy of the model may decline in some cases. Nonetheless, in certain fields—such as text mining and medical data analysis—this assumption does not pose a major problem [31-33].

D. XGBOOST ALGORITHM (EXTREME GRADIENT BOOSTING)

XGBoost (eXtreme Gradient Boosting) is a powerful ensemble learning algorithm based on decision trees, developed by Chen and Guestrin. It is a robust gradient-boosted decision tree (GBDT) method that constructs models in a sequential manner, where each new tree is optimized to correct the errors made by the previous trees, aiming to minimize the loss function. Compared to traditional GBDT approaches, XGBoost offers higher generalization performance, faster processing speed, and greater model flexibility.

XGBoost works by building decision trees sequentially, with each new tree focusing on minimizing the residual errors from the previous ones. The overall objective function optimized by the model can be expressed as follows:

$$L(\phi) = \sum_{i=1}^n l(y_i, \hat{y}_i^t) + \sum_{k=1}^t \Omega(f_k) \quad (11)$$

Here, $l(y_i, \hat{y}_i)$ represents the loss function that measures the prediction error (e.g., log loss or squared error), while $\Omega(f_k)$ is the regularization term that controls the complexity of the model. This regularization term is formulated as follows:

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \|\mathbf{w}\|^2 \quad (12)$$

Here, T represents the number of leaves in the tree, $\mathbf{w}$ denotes the leaf scores, and γ and λ are the regularization coefficients applied to model complexity and weight magnitude, respectively. This structure helps prevent overfitting and enhances the generalization capability of the model.

The performance of the XGBoost model heavily depends on the proper tuning of its hyperparameters. In this study, the following key hyperparameters were optimized for model configuration:

- **n_estimators:** The total number of decision trees to be constructed. More trees generally lead to better generalization but increase computational cost.
- **max_depth:** The maximum depth of each tree. Greater depth can create complex decision boundaries but may also lead to overfitting.
- **learning_rate:** The learning rate; it limits the contribution of each individual tree to the final model.
- **subsample** and **colsample_bytree:** The subsampling ratios for data and features, respectively; used to reduce overfitting and increase diversity among trees.

These hyperparameters were optimized using grid search and cross-validation methods [34-35].

E. PERFORMANCE METRICS

In classification systems developed using machine learning and artificial intelligence techniques, performance metrics play a critical role in quantitatively evaluating a model's predictive capabilities. These metrics offer a comprehensive understanding of the model's general performance as well as its ability to correctly classify individual categories. Among the most commonly employed and informative evaluation measures are accuracy, precision, recall, and F1-score. Each of these metrics captures different aspects of classification quality and is elaborated upon in the following sections.

Accuracy

Accuracy refers to the proportion of correctly classified instances among the total number of predictions made by the model. While it offers a straightforward and easily interpretable measure of overall performance, it may not always reflect true effectiveness—particularly in scenarios involving imbalanced class distributions. For example, a model that consistently misclassifies minority class samples might still report high accuracy, thereby providing an overly optimistic evaluation of its classification performance.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

Precision

Precision quantifies the accuracy of positive predictions by calculating the ratio of true positives to the total number of instances classified as positive by the model. This metric is particularly critical in domains where the consequences of false positives are significant—such as in industrial fault detection or medical diagnostics. A high precision value signifies that the model tends to be cautious in assigning positive labels, thereby ensuring that most identified positives genuinely belong to the target class.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (14)$$

Recall

Recall represents the percentage of true positive instances that the model successfully detects among all actual positive cases. This metric is especially vital in scenarios where missing a positive case—i.e., generating a false negative—can have serious consequences, such as in safety-critical systems or medical diagnoses. A high recall score reflects the model's strong ability to capture relevant positive examples, ensuring minimal oversight in identifying the target condition or class.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (15)$$

F1 Score

The F1 score serves as the harmonic mean of precision and recall, offering a balanced measure that considers both metrics simultaneously. It is especially advantageous in scenarios with imbalanced datasets or when it is equally important to minimize both false positives and false negatives. A high F1 score signifies that the model performs well in accurately identifying positive instances while also maintaining a low rate of misclassification.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (16)$$

Taken together, these metrics provide a more detailed and reliable evaluation of a classification model's overall performance and its ability to make accurate predictions across different classes [36-37].

V. FINDINGS

In this section, the performance of different machine learning algorithms used for bearing fault classification is evaluated. Based on signals obtained from the Case Western Reserve University (CWRU) bearing dataset, the Random Forest, XGBoost, SVM, and Naive Bayes algorithms were applied. Each model was analyzed in detail in terms of accuracy, precision, recall, and F1-score metrics. Additionally, performance comparisons were visualized and evaluated based on signal type and feature type. Assessing model performance not only at the algorithm level but also in terms of feature types (mean, max, min, sd, rms, skewness, kurtosis, crest, and form) is of great importance in identifying which statistical features are more decisive in fault diagnosis. The classification success rates obtained using the four machine learning methods are presented in Table 5.1.

TABLE 5.1 PERFORMANCE COMPARISON OF CLASSIFICATION MODELS

Model	Accuracy	precision	recall	f1-score
Random Forest	0.9573	0.96	0.96	0.96
SVM	0.9373	0.94	0.94	0.94
Naive Bayes	0.9240	0.93	0.92	0.92
XGBoost	0.9573	0.96	0.96	0.96

As shown in Table 5.1, based on the performance results, the most successful classification models are Random Forest and XGBoost. Both models stand out with an accuracy of 95.73%

and precision, recall, and F1-score values of 96%. These results indicate that the models demonstrate high performance in terms of making correct classifications overall.

The Support Vector Machine (SVM) algorithm, with an accuracy rate of 93.73%, emerges as a stable and reliable alternative. With each of its precision, recall, and F1-score values at 94%, SVM shows a strong capability to distinguish between classes and possesses a high generalization ability. In contrast, the Naive Bayes model performs lower compared to the other algorithms. Although it achieved 92.40% accuracy, along with 93% precision and 92% recall and F1-score, the model still demonstrates acceptable performance in basic classification tasks. However, due to its conditional independence assumption, this model may have limitations, especially when dealing with complex and high-dimensional datasets.

In conclusion, the evaluation results suggest that the Random Forest and XGBoost models provided the highest classification performance on the dataset used in this study and can be considered the most suitable methods for accurately diagnosing bearing faults.

The bar chart in Figure 5.1 below presents a comparison of the four classification models (Random Forest, SVM, Naive Bayes, and XGBoost) in terms of the four key performance metrics: accuracy, precision, recall, and F1-score. The graph provides a visual comparison of each model's performance level across each metric.

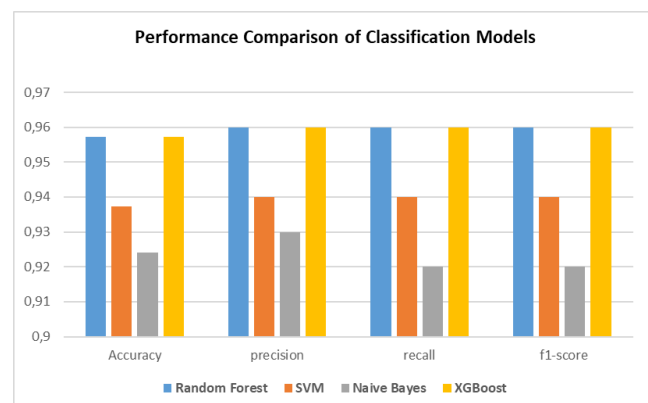


Figure 5. 1 Performance Comparison of Random Forest, SVM, Naive Bayes, and XGBoost Models

In Table 5.1, the overall performance of different classification algorithms was compared, and it was observed that the Random Forest and XGBoost models achieved the highest accuracy. This evaluation demonstrated the overall accuracy and classification capability of the models across the entire dataset. In Table 5.2, this general assessment is further detailed by presenting the performance metrics of the Random Forest model for each specific fault type (e.g., IR_007_1, Ball_021_1).

As shown in Table 5.2, the Random Forest model achieved 100% accuracy, precision, recall, and F1-score for the signals IR_007_1, IR_014_1, IR_021_1, and Normal_1. These results indicate that the model was able to classify these signal types almost flawlessly. In particular, the 100% recall rate for the "normal" signal suggests that the model is highly

successful in accurately identifying the healthy (non-faulty) condition.

TABLE 5. 2 SIGNAL-BASED CLASSIFICATION PERFORMANCE OF THE RANDOM FOREST MODEL

Signal	Accuracy	precision	recall	f1-score
Ball_007_1	0.96	0.97	0.96	0.97
Ball_014_1	0.88	0.92	0.88	0.90
Ball_021_1	0.8667	0.90	0.87	0.88
IR_007_1	1.00	1.00	1.00	1.00
IR_014_1	1.00	1.00	1.00	1.00
IR_021_1	1.00	1.00	1.00	1.00
Normal_1	1.00	1.00	1.00	1.00
OR_007_6_1	1.00	0.99	1.00	0.99
OR_014_6_1	0.8933	0.84	0.89	0.86
OR_021_6_1	0.9867	0.97	0.99	0.98

However, performance drops were observed for signals such as Ball_014_1, Ball_021_1, and OR_014_6_1. For example, in the Ball_021_1 class, the accuracy drops to 86.67%, and there are discrepancies between precision and recall values. This implies that the model misclassified some samples in these classes, confusing them with other fault types. Overall, while the model performs with very high accuracy on "inner race" (IR) and "outer race" (OR) faults, it shows variable performance on "ball" type faults depending on the signal characteristics.

Figure 5.2 below illustrates the classification accuracy rates obtained by the model for each bearing fault class. The model reaches 100% accuracy for IR_007_1, IR_014_1, IR_021_1, and Normal_1, demonstrating highly effective classification for these classes.

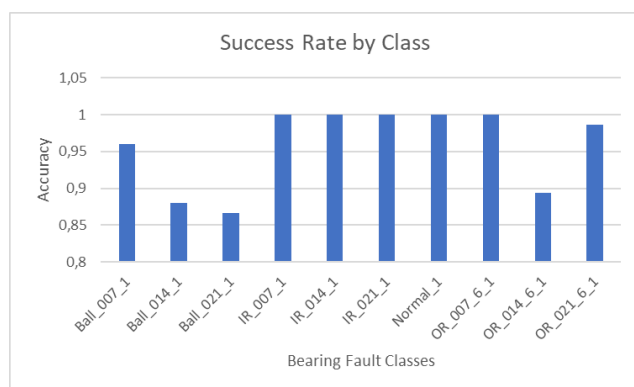


Figure 5. 2 Classification Accuracy Rates for Each Fault Signal Class

Confusion matrices are provided to illustrate the class-wise performance of different models. These matrices clearly reveal in which classes the models make more errors and in which they perform strongly. Figure 5.3 presents the confusion matrices for the models used.

As shown in Figure 5.3, the Random Forest and XGBoost models distinguish IR and OR signals with high accuracy, while the Naive Bayes model demonstrates comparatively lower performance for the Ball class than the other models. As shown in Table 5.3, the results indicate that the highest classification performance was achieved using the standard

deviation (sd) feature. This feature demonstrated superior performance in terms of both accuracy and F1-score compared to the other features.

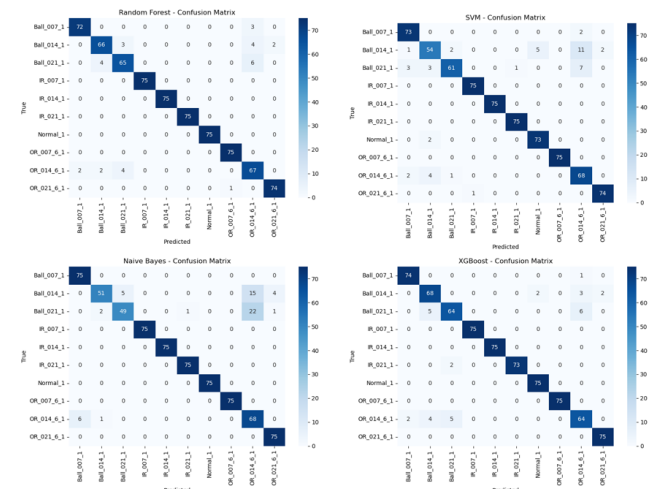


Figure 5. 3 Comparison of Confusion Matrices for Four Different Classification Models

An important contribution of this study is the performance analysis conducted at the feature level. Table 3 below presents the classification performance of fundamental statistical features used in bearing fault diagnosis, evaluated using the Random Forest algorithm. Each feature was individually tested in the model, and its performance was measured using accuracy, precision, recall, and F1-score metrics. The results are provided in Table 5.3.

TABLE 5. 3 FEATURE-BASED PERFORMANCE EVALUATION OF RANDOM FOREST CLASSIFICATION

Feature	Accuracy	precision	recall	f1-score
max	0.578261	0.574589	0.578261	0.575498
min	0.565217	0.551416	0.565217	0.556578
mean	0.285507	0.284134	0.285507	0.283265
sd	0.628986	0.634502	0.628986	0.629776
rms	0.615942	0.618286	0.615942	0.616016
skewness	0.24058	0.248969	0.24058	0.24235
kurtosis	0.386957	0.382938	0.386957	0.380831
Crest	0.275362	0.270234	0.275362	0.271135
form	0.457971	0.461526	0.457971	0.457787

Similarly, the Root Mean Square (rms) feature also yielded high performance, highlighting that the overall energy level of the signal plays a significant role in fault classification. On the other hand, features such as skewness and mean provided the lowest classification performance. This suggests that these features may be insufficient for distinguishing bearing faults and do not offer meaningful discrimination when used alone. Additionally, features like kurtosis and form factor were observed to exhibit moderate performance levels.

Figure 5.4 below presents the feature importance rankings in the classification processes of the RF and XGBoost models. This comparative analysis is particularly significant from a

computational cost perspective, as it enables the identification of the most effective features that enhance model performance.

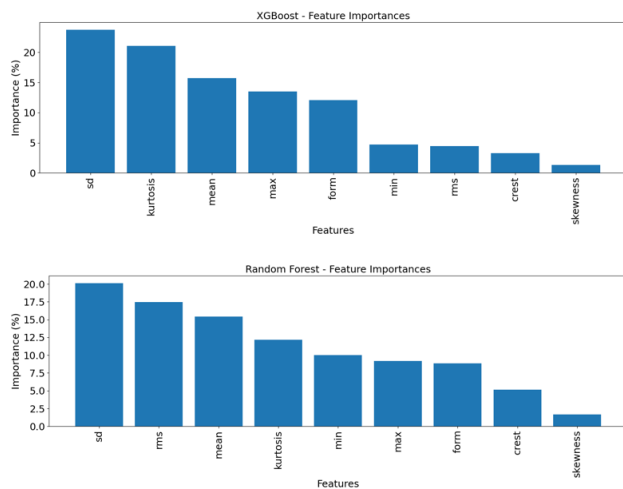


Figure 5. 4 Comparison of Feature Importance Rankings According to XGBoost and Random Forest Models

A common finding in both the RF and XGBoost models is that the standard deviation (sd) feature holds the highest importance score. This indicates that the "sd" feature, which represents the dispersion and variance in the data, is a highly decisive factor in distinguishing bearing faults. In the XGBoost model, features such as kurtosis, mean, max, and form exhibit high importance scores, whereas features like skewness, crest, rms, and min contribute relatively less. Notably, skewness is considered the least contributing feature by XGBoost. In the Random Forest model, following sd in importance are rms, mean, kurtosis, and min. Similarly, skewness and crest are identified as the least important features in this model as well.

VI. DISCUSSION AND CONCLUSION

In this study, a comparative analysis of different machine learning algorithms for the diagnosis of bearing faults was conducted. As emphasized in the introduction, bearings are critical components for the continuity and safety of mechanical systems. Failure to detect bearing faults in a timely manner can lead to reduced operational efficiency and significant economic losses. To overcome the limitations of traditional signal processing-based methods, machine learning and deep learning techniques have gained increasing importance in recent years. The study utilized the Case Western Reserve University (CWRU) dataset and applied four classification algorithms: Random Forest (RF), Support Vector Machine (SVM), Naive Bayes (NB), and XGBoost. The findings revealed that Random Forest and XGBoost achieved the best performance, each with an accuracy of 95.73% and precision, recall, and F1-score values of 96%. These results indicate that both algorithms possess high generalization capability and strong discriminative power for fault classification. The SVM algorithm demonstrated stable performance with an accuracy of 93.73%, while the Naive Bayes algorithm performed comparatively worse, primarily due to its assumption of conditional independence between

features. The results also showed notable differences in model performance depending on the fault type. Inner race (IR) and outer race (OR) faults could be classified with up to 100% accuracy, whereas ball-type faults exhibited decreased success rates depending on signal strength. This suggests that the signal characteristics of certain fault types are more easily distinguishable by classification models.

Moreover, the feature-level analysis highlighted that standard deviation (sd) and root mean square (RMS) are the most decisive features in bearing fault diagnosis. In contrast, features such as mean, skewness, and crest contributed less to classification performance. The feature importance rankings produced by both RF and XGBoost models supported these findings, confirming that features based on signal variance play a leading role in fault classification. In conclusion, this study not only demonstrated the effectiveness of various machine learning algorithms in bearing fault diagnosis but also systematically analyzed which signal features are more influential in the classification process. Ensemble learning-based models like Random Forest and XGBoost emerged as the most suitable methods due to their robust generalization capabilities and feature selection strengths. Future work may focus on hybridizing these models with deep learning architectures, testing on different datasets, and integrating into real-time predictive maintenance systems to further enhance the efficiency of bearing health monitoring.

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