Advanced Signal Decomposition and Ensemble Learning for Sustainable Maintenance: A Case Study on Bearing Faults

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Abstract. Early fault detection in rolling bearings is a critical challenge in predictive maintenance due to the weak, nonstationary nature of fault-induced vibration signals and the presence of significant background noise in industrial environments. Traditional signal processing and classification techniques often struggle to isolate fault-relevant features under such conditions, leading to reduced diagnostic accuracy and poor generalization. This study proposes a hybrid diagnostic framework that combines Variational Mode Decomposition (VMD) for adaptive signal decomposition with Extreme Gradient Boosting (XGBoost) for accurate fault classification. VMD effectively mitigates mode mixing and extracts discriminative features by decomposing the signal into band-limited intrinsic mode functions, while XGBoost handles high-dimensional feature spaces with robustness to noise and overfitting. The proposed method demonstrates superior performance in both accuracy and interpretability compared to conventional models, offering a scalable solution for realtime condition monitoring. This work contributes to the advancement of intelligent maintenance systems and supports sustainable operation in complex, data-scarce industrial settings such as smart manufacturing and renewable energy sectors.

Keywords: Fault Diagnosis · Rotating Machinery · Machine Learning · Predictive Maintenance · Sustainable Manufacturing

1 Introduction

In modern industry, mechatronic systems are becoming increasingly complex and expensive, particularly in fields such as smart manufacturing and renewable energy [3]. To maintain the stability, safety, and operational efficiency of these systems, effective condition monitoring (CM) programs and maintenance strategies are critically important. Unexpected failures can result in significant downtime, workplace accidents, and substantial financial losses, with operation and maintenance (O&M) costs accounting for 15% to 60% of total production expenses, depending on the industry [1]. Therefore, the adoption of advanced maintenance strategies not only extends the useful lifespan of equipment, reduces costs, and minimizes electronic waste, but also contributes to the goals of sustainable manufacturing and efficient energy management [24]. The emergence of the Internet of Things (IoT) and machine learning (ML) has opened new opportunities for real-time monitoring and fault diagnosis in industrial environments [33, 25].

Rolling bearings are among the most critical and failure-prone components in rotating machinery [25]. They play a fundamental role in ensuring the smooth and reliable operation of mechanical systems across a wide range of industrial sectors. In the manufacturing industry, bearings are essential in machine tools, steel production lines, and conveyor systems. In the energy sector, they are integral to power generation equipment such as generators and wind turbines [12]. Similarly, in the transportation sector, bearings are widely used in aircraft engines, railway switch mechanisms, and locomotives [23, 7]. Bearing-related failures can lead to severe operational issues, accounting for an estimated 40% to 90% of total machinery breakdowns, depending on motor size [25]. Early fault diagnosis in rolling bearings is therefore critical for preventing catastrophic failures, minimizing investment losses, and enhancing the accuracy of predictive maintenance models. However, early fault detection in rolling bearings remains a significant challenge due to several critical factors [9]. In the early stages of degradation, fault-related vibration signals are typically weak, indistinct, and often masked by ambient noise, making them difficult to isolate and interpret [34]. Moreover, the dynamic nature of industrial environments, where operating conditions such as speed, load, and temperature vary continuously can significantly affect the characteristics of diagnostic signals, thereby reducing the reliability of conventional analysis techniques [24]. Additionally, many traditional and data-driven approaches rely heavily on large volumes of labeled training data, which are often unavailable or difficult to obtain in real-world settings [11, 32]. These limitations underscore the need for more advanced diagnostic frameworks that are sensitive to subtle signal variations, robust to environmental noise, and capable of generalizing across variable operating conditions with limited supervision.

To overcome these challenges, vibration signal analysis is regarded as one of the most effective and widely used approaches for condition monitoring and predictive maintenance, as it provides valuable insights into the dynamic behavior of machinery. Vibration signals carry rich information about the dynamic behavior of machinery and are highly sensitive to mechanical faults, making them particularly valuable for early fault detection and health assessment of rotating components [4]. In recent years, data - driven approaches particularly those based on deep learning have brought significant advancements in machinery fault diagnosis [24]. However, to effectively handle non-stationary and noise contaminated vibration signals, advanced signal preprocessing and classification techniques remain essential. These techniques play a critical role in enhancing the quality of extracted features and improving the overall reliability of fault detection systems.

Handling noise and nonstationarity in vibration signals has driven the development of a variety of advanced signal processing techniques [21]. Initially, traditional approaches such as the Fourier Transform (FT) were widely employed to transform signals into the frequency domain to identify characteristic frequencies associated with bearing faults. However, in high-noise environments, weak fault features may be completely masked by strong noise and unrelated frequency components [18]. To address the limitations of traditional methods that analyze signals only in the time or frequency domain, time-frequency domain techniques have been developed, providing a more comprehensive view of signal evolution over time and frequency. Wavelet Transform (WT) and Short-Time Fourier Transform (STFT) are two of the most widely used time-frequency analysis methods. WT offers multi-resolution analysis, allowing signals to be examined at various frequency bands with adjustable time and frequency localization [19]. This makes it well-suited for detecting abrupt changes and transient features in vibration signals. However, the effectiveness of WT largely depends on the appropriate selection of the mother wavelet, which directly affects the ability to isolate relevant fault-related components [2]. STFT, on the other hand, partitions the signal into short time segments using a fixed-size window, and applies the Fourier Transform to each segment. This approach enables the observation of frequency variations over time but suffers from the inherent trade-off between time and frequency resolution due to the fixed window size [31]. As a result, STFT may struggle to accurately capture fast-changing or broadband fault features, especially in complex machinery systems.

Empirical Mode Decomposition (EMD) and its variants, such as Ensemble EMD (EEMD) and Complementary EEMD with Adaptive Noise (CEEMDAN), have been widely used for analyzing nonlinear and nonstationary vibration signals by adaptively decomposing them into Intrinsic Mode Functions (IMFs) [29, 23, 22]. These methods have proven effective in many condition monitoring tasks due to their data-driven nature and ability to reveal localized signal features. However, EMD-based approaches commonly suffer from mode mixing, where distinct frequency components are either merged into a single IMF or split across multiple modes. This significantly reduces the interpretability of the results and hinders the isolation of weak fault-related features from background noise [15]. Despite efforts to improve EMD, such as adding white noise in EEMD or applying refined decomposition strategies in CEEMDAN, mode mixing and sensitivity to noise remain key limitations [22]. Moreover, these methods often lack strong mathematical foundations and require heuristic post-processing, which may reduce reliability in practical applications.

Variational Mode Decomposition (VMD) was developed as a solution to overcome the drawbacks of traditional decomposition techniques—particularly the mode mixing issue in EMD [29]. Proposed in 2014, VMD formulates the decomposition problem as a constrained variational optimization task that separates a signal into a finite number of band-limited IMFs, each localized around a center frequency [23]. Unlike EMD, VMD minimizes the overall bandwidth of the modes, effectively suppressing mode mixing and enhancing the separation of closely spaced or weak fault components even in high-noise conditions. Furthermore, VMD operates in a non-recursive and adaptive manner, making it particularly well-suited for analyzing complex, nonlinear, and nonstationary signals commonly found in bearing fault diagnosis. One of the key advantages of VMD lies in its tunable parameters—specifically the number of modes (K) and the penalty factor (α)—which allow flexible control over the decomposition resolution [15]. With proper parameter selection, VMD achieves high fidelity in isolating fault-induced features while reducing interference from irrelevant frequency components. Additionally, extensions such as Short-Time VMD (STVMD) enable the tracking of time-varying spectral behavior with low reconstruction error, further improving diagnostic performance [14]. Given its effectiveness in isolating weak fault signatures and its adaptability to various signal types, VMD represents a significant advancement in vibration signal analysis. It establishes a solid foundation for reliable fault diagnosis and condition monitoring in rotating machinery systems.

Following the extraction of representative features from vibration signals using advanced signal processing techniques such as VMD, an essential step in fault diagnosis involves the application of effective classification algorithms. A wide range of machine learning methods have been explored in this domain, including classical models like Support Vector Machines (SVM), Decision Trees (DT), and ensemble techniques such as Random Forests (RF) [25, 12].However, these classical models often struggle when dealing with large-scale or high-dimensional feature sets, as they rely on handcrafted features and lack the scalability required for complex data distributions. This limits their effectiveness in real-world industrial applications where feature sets can be large, redundant, or highly nonlinear. In recent years, deep learning models especially Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures have been employed to automatically learn complex patterns from raw or preprocessed signals [4]. Despite their impressive performance, these models typically require large volumes of labeled data, high computational resources, and are often criticized for their lack of interpretability [20]. These limits their effectiveness in real-world industrial applications.

To address these limitations, this study proposes the use of Extreme Gradient Boosting (XGBoost) as the core classification algorithm. XGBoost is an optimized implementation of gradient boosting decision trees, designed for high accuracy, computational efficiency, and scalability [6]. It employs an additive training strategy where decision trees are constructed sequentially to minimize a regularized objective function. The incorporation of both first- and second-order gradients enables faster convergence and improved generalization. Moreover, XGBoost includes built-in mechanisms for handling missing data, preventing overfitting via shrinkage and column subsampling, and supports parallel processing, making it highly suitable for large-scale industrial datasets.

In summary, existing studies combining signal decomposition with machine learning still leave three practical gaps: (1) building noise-resilient, nonstationary features with clear mathematical grounding; (2) using ensemble learning that retains feature-level interpretability rather than black-box inference; and (3) task-specific, reproducible parameterization of both decomposition and classifier that respects computational budgets for deployment. In this work, XGBoost is integrated with VMD-based feature extraction to build a robust and interpretable diagnostic framework. Variational Mode Decomposition (VMD) provides band-limited intrinsic mode functions (IMFs) with explicit control via K (number of modes) and α (bandwidth penalty), enabling adaptive, noise-robust decomposition and mathematically well-posed feature construction. From both IMF-level signals and an energy-aware reconstruction (retaining high-energy IMFs), we extract time- and frequency-domain descriptors that capture amplitude dynamics, spectral localization, and entropy-like complexity. These features are classified by XGBoost, a boosting-based ensemble of CART trees that combines strong accuracy with built-in regularization and feature-importance interpretability. Together, this design addresses the above gaps by pairing principled decomposition with an efficient, explainable ensemble classifier. This framework is particularly valuable for condition monitoring applications in noisy and variable industrial environments, contributing to the development of smart, sustainable maintenance systems.

2 Theoretical Basis

2.1 Principles of VMD

VMD is an advanced signal decomposition technique proposed by Dragomiretskiy and Zosso, aiming to decompose a complex signal into a set of oscillating components called IMFs with narrow frequency bands [30]. Each IMF is assumed to have slowly varying amplitude and frequency (AM-FM) and its spectrum is centered around a specific central frequency. Unlike EMD, VMD processes modes simultaneously rather than sequentially and is defined based on a well-defined variational optimization problem.

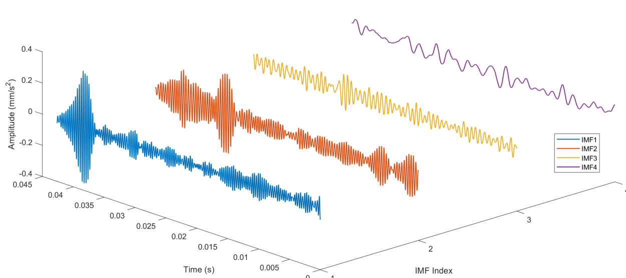

Fig. 1. Schematic illustration of the Variational Mode Decomposition (VMD) process

One of VMD's outstanding advantages is its superior noise handling capability. Thanks to its global optimization mechanism and explicit mathematical model, VMD can isolate noise components from the original signal without distorting the main modes. When an appropriate penalty factor is used, and in cases where complete signal reconstruction is not required, VMD can effectively function as a powerful adaptive filter, especially in high-noise vibration environments, such as real-world mechanical systems.

The objective of VMD is to find an ensemble of modes $u_k(t)$ and their corresponding central frequencies ω_k such that the original signal $f(t)$ can be accurately reconstructed [8]:

$$f(t) = \sum_{k=1}^{K} u_k(t) \tag{1}$$

Each mode is demodulated to its baseband via spectral shifting to its central frequency w_k, and then its bandwidth is estimated according to the L^2 norm of the gradient of the demodulated signal. The variational optimization problem is given by:

$$\min_{\{u_k,\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \quad s.t. \quad \sum_k u_k = f \tag{2}$$

In this equation, the convolution with $\left(\delta(t) + \frac{j}{\pi t}\right)$ corresponds to the Hilbert transform, yielding the analytic signal. This optimization problem is solved using the augmented Lagrangian function:

$$\begin{aligned} \mathcal{L}(u_k, \omega_k, \lambda) =& \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \\ &+ \left\| f - \sum u_k \right\|_2^2 + \langle \lambda, f - \sum u_k \rangle \end{aligned} \tag{3}$$

Where α is the penalty factor that controls spectral compactness and λ is the Lagrangian multiplier. This problem is solved using the alternating direction method of multipliers (ADMM), which involves the following steps:

- Update of mode u_k:

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i<k} \hat{u}_i^{n+1}(\omega) - \sum_{i>k} \hat{u}_i^{n}(\omega) + \frac{\hat{\lambda}^n(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k^n)^2} \tag{4}$$

- Update of central frequency ω_k:

$$\omega_k^{k+1} = \frac{\int_0^\infty \omega |\hat{u}_k^{n+1}(\omega)|^2 \, d\omega}{\int_0^\infty |\hat{u}_k^{n+1}(\omega)|^2 \, d\omega} \tag{5}$$

- Update of Lagrangian multiplier λ:

$$\hat{\lambda}^{n+1}(\omega) = \hat{\lambda}^n(\omega) + \tau \left(\hat{f}(\omega) - \sum_k \hat{u}_k^{n+1} \right) \tag{6}$$

The iteration process stops when the relative change of the modes is smaller than a convergence threshold ε.

To ensure optimal and robust VMD results, the algorithm's parameters were meticulously selected based on both theoretical considerations, empirical observations from the input signal's spectral characteristics, and practical experience.

- Number of Modes, K: K is a critical parameter influencing VMD performance. A small K can lead to mode mixing, where distinct frequency components are incorrectly grouped into a single IMF. Conversely, an excessively large K may result in over-decomposition, generating spurious modes lacking physical meaning.
- Penalty Factor, α: The penalty factor α governs the bandwidth constraint of extracted IMFs, directly influencing their spectral compactness. A large α promotes narrow bandwidths, effective for noise suppression, but risks over-smoothing or removing genuine weak components. A small α allows for broader bandwidths, risking mode mixing.
- Convergence Criterion: The iterative optimization process of VMD was terminated when the relative change between successive iterations of the modes fell below a stringent convergence threshold of 10^{-7}. This criterion ensures that the decomposition has fully converged, leading to highly stable and consistent IMFs, thereby minimizing computational artifacts.
- Signal Windowing: Prior to VMD decomposition, each signal segment was multiplied by a Gaussian window. This preprocessing step is crucial for minimizing spectral leakage and boundary effects that can arise from the implicit Fourier transform within the VMD algorithm, thereby enhancing the accuracy and quality of the resulting spectral decomposition.

2.2 XGBoost-based Classification Method

XGBoost is an advanced and optimized implementation of the gradient boosting framework. It sequentially builds an ensemble of decision trees, where each new tree aims to correct the errors (residuals) of the preceding ensemble. Its strength lies in sophisticated regularization techniques, intrinsic handling of missing values, and parallel processing capabilities, making it highly suitable for the complex, large-scale datasets often encountered in industrial fault diagnosis [10].

XGBoost operates by iteratively adding new decision trees to an ensemble, with each new tree trained to correct the errors made by the preceding trees. This additive modeling approach is formalized by minimizing a regularized objective function. This function combines a traditional differentiable loss function with regularization terms. These regularization terms ($L1$ and $L2$, controlled by α and λ respectively) penalize model complexity, specifically the number of leaves and the magnitude of leaf weights, thereby controlling overfitting and improving generalization performance. This is a crucial aspect for real-world fault diagnosis, where data can be noisy, limited, or exhibit complex distributions.

The objective function for XGBoost at iteration t can generally be expressed as [26]:

$$Obj^{(t)} = \sum_{i=1}^{n} L(y_i, \hat{y}i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \tag{7}$$

where l is the differentiable loss function, y_i is the true label, $\hat{y}_i^{(t-1)}$ is the prediction from the $(t-1)$-th tree, $f_t(x_i)$ is the new tree added at iteration t, and $\Omega(f_t)$ is the regularization term for the new tree. XGBoost internally optimizes by leveraging first and second-order gradient statistics of the loss function (via a second-order Taylor expansion) to optimize the objective. This approach leads to faster convergence and more powerful optimization compared to traditional gradient boosting algorithms.

The regularization terms (L1 and L2) penalize model complexity, specifically the number of leaves and the magnitude of leaf weights, thereby controlling overfitting and improving generalization performance.

- L1 Regularization: Controlled by the parameter α. L1 regularization adds the absolute value of the feature weights to the loss function, encouraging models to be sparse by setting some feature weights to zero. A higher α value leads to more feature weights being set to 0, resulting in a simpler model that is easier to interpret.
- L2 Regularization: Controlled by the parameter λ. L2 regularization adds the squared magnitude of the feature weights to the loss function. Unlike L1, L2 encourages smaller weights across all features rather than setting them to zero. A higher λ value leads to smaller weights and a simpler model, which can also help control overfitting.
- Gamma (γ) Parameter: Also known as the minimum loss reduction parameter, γ controls the minimum loss reduction required to make a further partition on a leaf node of the tree. A higher γ value makes the algorithm more conservative, avoiding partitions that do not significantly improve the objective function, thereby controlling the complexity of the tree and preventing overfitting.

The base learners are Classification and Regression Trees (CART), which are trained sequentially. Each tree focuses on the residual errors of the previous stage, and the final model is obtained by aggregating the weighted contributions of all trees in an additive manner. For multi-class classification tasks, the suitable objective function in XGBoost would be $softmax$ for predicting discrete class labels, or $softprob$ for predicting class probabilities. Due to the requirement of identifying specific fault types, $softmax$ is typically used for direct classification results, while $softprob$ can provide additional confidence measures for each class, which can be valuable for making quantitative or uncertain decisions.

Compared to "black-box" deep learning models, XGBoost offers better interpretability, which is crucial for engineers to trust and troubleshoot diagnostic systems. The tree-based nature of XGBoost means that the prediction rules from a single decision tree can be easily extracted, making it more interpretable [28].

3 Proposed Intelligent Fault Diagnosis Framework

3.1 Signal Acquisition and Preprocessing

Signal acquisition and preprocessing are fundamental stages within the entire fault diagnosis framework, ensuring the quality and reliability of the data. Vibration signals were acquired from faulty bearings using accelerometers. A high sampling frequency was often employed to ensure that high-frequency components, up to the natural frequency of the bearing, were captured. Each acquired signal was subsequently segmented into 2048-point frames. This segmentation aims to ensure a short observation time, increase the consistency in batch processing, and facilitate analysis in both time and frequency domains.

To enable reliable classification of bearing fault conditions, a comprehensive feature extraction strategy is applied based on the decomposition results obtained from VMD. Each vibration signal segment is first decomposed into K IMFs. The diagnostic information is then derived from both the individual IMFs and a reconstructed signal formed by selectively combining IMFs with significant energy contributions.

3.2 Feature Extraction from IMFs

After the vibration signals have been preprocessed, they are fed into VMD to obtain a set of IMFs. VMD's ability to adaptively decompose non-stationary and non-linear signals into a set of band-limited and approximately-sparse IMFs, while simultaneously minimizing the adverse effects of noise, makes it an ideal tool for extracting relevant fault features.

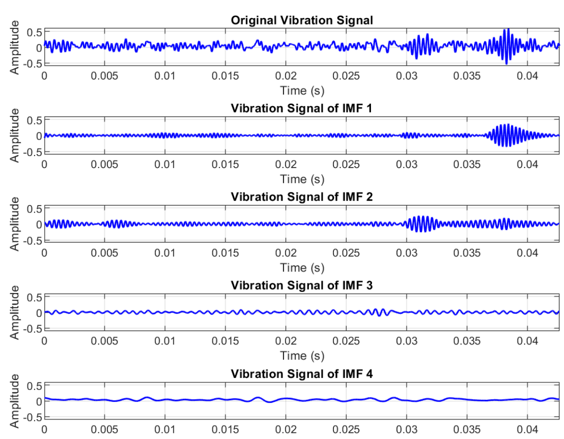

Fig. 2. Time-domain VMD decomposition of the original vibration signal

From these IMFs, various statistical features are computed.We extracting the following features:

- Time-domain Features: Root Mean Square, Kurtosis, Skewness, Peak-to-Peak, Crest Factor, Shannon Entropy. These features quantitatively describe the amplitude distribution and variability of each IMF [28].
- Frequency-domain Features: Spectral Entropy, Mean Frequency, Median Frequency, Peak Frequency, Spectral Centroid, Spectral Spread, Spectral Flatness. These features characterize the spectral properties of each IMF, offering comprehensive insights into the dominant frequencies and their distribution across the modes.

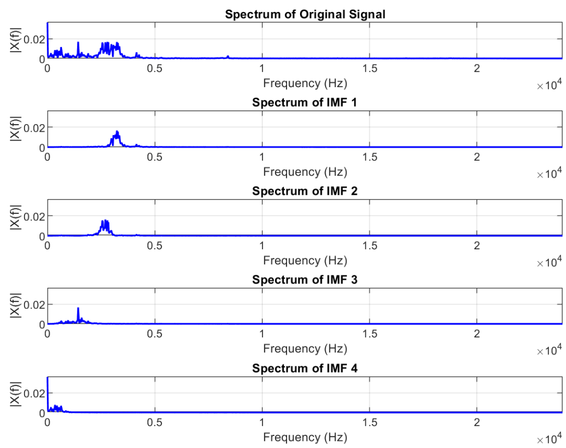

Fig. 3. Frequency-domain VMD decomposition of the original vibration signal

Extracting features from individual IMFs, rather than solely from the raw signal, is paramount for analyzing complex, non-stationary signals. Each IMF represents a distinct oscillatory component at a specific frequency scale, enabling a multi-scale view of the signal. This approach allows for the capture of localized characteristics and transient dynamics that might otherwise be obscured or averaged out in the aggregate raw signal. By analyzing each IMF separately, researchers can gain detailed insights into the signal's behavior across different frequency bands, which is crucial for effective pattern recognition and classification.

3.3 Feature Extraction from Signal Reconstruction

In addition to analyzing the full set of IMFs, a reconstructed signal is generated by summing only the IMFs that carry significant energy, defined as those whose energy exceeds a threshold of 5% of the total signal energy. This threshold was determined through empirical observation and statistical analysis across multiple signal samples, where it was found that most noise-dominated IMFs tend to contribute less than 5% of the total energy. As a result, this threshold effectively preserves fault-relevant modes while filtering out low-energy components typically associated with noise or insignificant fluctuations.

For a discrete signal or a specific IMF $u_k[n]$ (where n is the sample index), the energy E_k is typically calculated as the mean squared amplitude of the mode across its entire length:

$$E_k = \sum_{n=1}^{N} |u_k[n]|^2 \tag{8}$$

where N is the total number of samples. This formula represents the total energy contained within the corresponding mode.

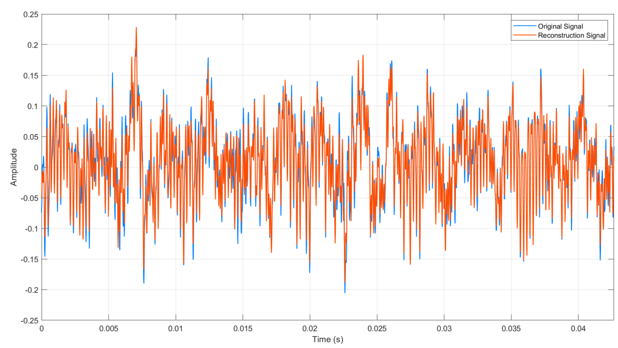

Fig. 4. Original vibration signal and reconstructed signal after VMD-based denoising.

This reconstructed signal is then used to extract the same set of time- and frequency-domain features as applied to individual IMFs. These features are subsequently combined with the IMF-level features to form a comprehensive feature vector, which is used to train and test the classification model.

3.4 XGBoost Fault Classification

After constructing a comprehensive feature matrix by concatenating IMF-level and reconstructed-signal features, the final step in our diagnostic pipeline is to train and evaluate an XGBoost classifier to automatically distinguish between bearing health conditions.

The overall classification process is illustrated in Figure 5, which outlines the architecture of the proposed diagnostic framework.

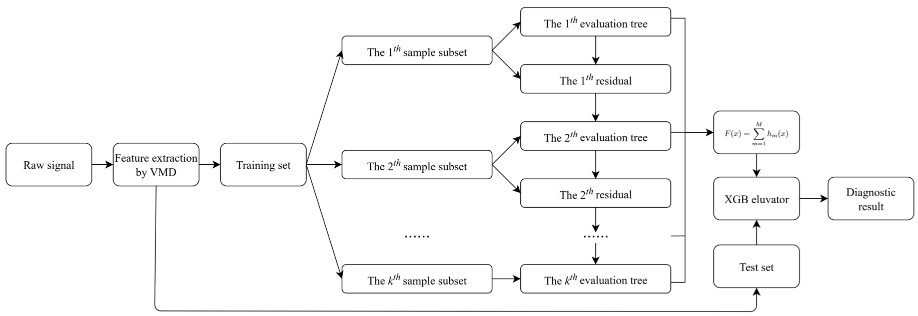

Fig. 5. Flowchart of the proposed VMD–XGBoost fault classification framework.

First, the features extracted from each IMF and the reconstructed signal are concatenated into a unified feature vector. These vectors, along with their corresponding fault labels, form the training dataset. Prior to model training, feature standardization is applied using z-score normalization to ensure consistency in scale across different dimensions.

The XGBoost algorithm proceeds by sequentially building an ensemble of regression trees. At each iteration, a new tree is fitted to the residual errors of the current ensemble, effectively correcting its predecessor's mistakes. Each training sample subset contributes to a weak learner (evaluation tree), and the final prediction function is obtained by aggregating the outputs of all K trees:

Once trained, the final XGBoost model—referred to here as the XGB evaluator—is used to infer the fault class of unseen test samples. The predicted class label serves as the final diagnostic result.

This VMD–XGBoost integration enables the construction of a high-performance, interpretable, and scalable fault diagnosis system. The use of VMD ensures that signal decomposition is adaptive and noise-resilient, while the gradient-boosted decision trees provide strong classification capabilities, particularly in the presence of complex, high-dimensional feature spaces.

4 Experimental and Results

4.1 Experimental Data Description

The experimental data used in this study are obtained from the well-known Case Western Reserve University (CWRU) Bearing Dataset [5], which has been widely adopted for benchmarking bearing fault diagnosis algorithms. The test rig consists of a 2 HP induction motor coupled with a torque transducer and a dynamometer. Vibration signals are acquired via accelerometers mounted at the drive-end and fan-end bearing housings of the motor. The bearings used in the testbed are SKF 6205-2RSJEM deep groove ball bearings.

To reflect diverse industrial conditions, the motor is operated under four load levels: 0, 1, 2, and 3 horsepower (HP), and at four different rotational speeds:

1797, 1772, 1750, and 1730 revolutions per minute (rpm). Faults are introduced into the bearings using Electrical Discharge Machining (EDM) and include three types:

- Inner race fault (IR)
- Outer race fault (OR)
- Ball fault (BA)

Each fault type is tested with three fault diameters (7, 14, and 21 mils), and healthy bearing data are also recorded to form the baseline class (N). All signals are sampled at 48,000 Hz, and acquired in a vibration-isolated chamber to ensure signal clarity and consistency.

A summary of the experimental conditions is presented in Table 1.

Table 1. Experimental conditions from the CWRU bearing dataset

Load(HP)	Speeds (rpm)	Fault Type	Fault Sizes(mils)	Class Label
0,1,2,3	1797,1772,1750,1730	Normal	0	N
0,1,2,3	1797,1772,1750,1730	Ball	7,14,21	BA
0,1,2,3	1797,1772,1750,1730	Inner Race	7,14,21	IR
0,1,2,3	1797,1772,1750,1730	Outer Race	7,14,21	OR

Each vibration signal is segmented into shorter samples of equal length, and features are extracted using the VMD-based method described in Section 3.2. The resulting labeled feature set is then randomly partitioned into a training set (80%) and a test set (20%). The training set is used to fit the XGBoost model, while the test set is reserved for independent evaluation of classification performance.

4.2 Parameter Selection

For the CWRU dataset, previous studies have shown that the performance of VMD depends significantly on the selection of the number of modes K and the penalty factor α. Referring to these works and considering the need to keep the computational cost reasonable for practical applications, we restricted the parameter search to a limited range of K and α values:

- $K \in \{2, 3, 4, 5, 6, 7, 8\}$
- $\alpha \in \{1000, 1500, 2000, 2500, 3000\}$

To ensure a systematic and objective choice of hyperparameters, we applied GridSearchCV from scikit-learn with stratified 5-fold cross-validation. This procedure allowed each candidate configuration to be evaluated fairly across different subsets of the training data, thereby reducing the risk of overfitting to a particular partition. The search grid was designed to cover the most influential parameters of XGBoost:

- n_estimators ∈ {100, 200, 300}
- max_depth ∈ {5, 10, 15, 20, 25}
- learning_rate ∈ {0.01, 0.05, 0.1}
- subsample ∈ {0.8, 1.0}
- colsample_bytree ∈ {0.8, 1.0}

The final parameter configuration was selected according to the criterion of achieving the highest cross-validation accuracy on the training set

4.3 Result and Discussion

After determining the parameter ranges for VMD and XGBoost in Section 4.2, the next step is to evaluate how these configurations affect the diagnostic performance on the test set. Table 2 presents the classification accuracies obtained for different combinations of K and α.

Table 2. Classification accuracy (%) of the VMD–XGBoost framework under different values of K and α.

K \ α	1000	1500	2000	2500	3000
2	98.35%	97.81%	97.26%	97.08%	96.77%
3	98.41%	97.87%	98.11%	97.87%	97.87%
4	98.48%	98.72%	**98.97**%	98.29%	98.11%
5	98.84%	98.54%	98.29%	98.05%	97.87%
6	86.56%	86.81%	87.23%	85.22%	87.23%
7	95.62%	87.11%	91.48%	82.61%	82.24%
8	94.89%	93.73%	86.62%	85.65%	87.59%

It can be observed that the performance is generally stable across the tested ranges, with accuracy values consistently above 85%. However, the configuration K=4 and α=2000 achieves the highest accuracy of 98.97%, outperforming the other settings. This indicates that five modes provide a sufficient level of decomposition to separate the fault-related frequency bands, while the penalty factor of 1000 ensures stable bandwidth control without over-decomposition.

Based on this result, the configuration K=4, α=2000 was selected for further analysis. The classification results are visualized in the confusion matrix shown in Figure 6, with all values expressed as percentages of correctly or incorrectly classified samples per class.

As seen from the matrix, the proposed method achieves consistently high classification accuracy (98.97%) across all bearing fault conditions. Specifically:

- The healthy class (N) is identified with 100% accuracy, indicating the model's robustness in detecting the absence of faults.
- The ball fault (BA) class is correctly predicted in 98.80% of test samples, with minor misclassification into IR (1.00%) and OR (0.20%).

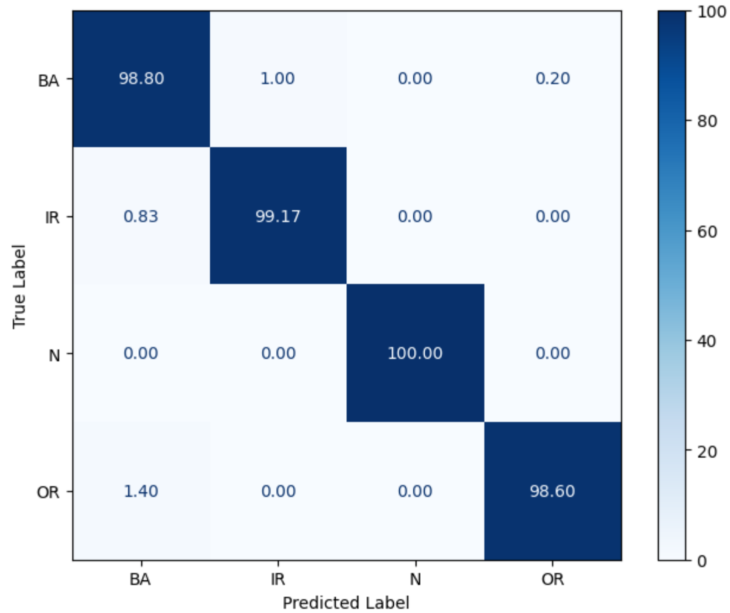

Fig. 6. Confusion matrix of test-set classification results

- The inner race fault (IR) class reaches an accuracy of 99.17%, with 0.83% of instances incorrectly labeled as BA.
- The outer race fault (OR) class is identified with 98.60% accuracy, with a small proportion (1.40%) misclassified as BA.

These results confirm the high precision and discriminative power of the feature set extracted via VMD, as well as the strong generalization capability of the XGBoost classifier. The overall classification accuracy on the test set reaches 98.97%, which is competitive with or superior to existing state-of-the-art approaches on the CWRU dataset. A baseline comparison with traditional classifiers shows that SVM and Random Forest typically reach around 95 – 97% [27, 16] accuracy on the CWRU dataset , and even with VMD-based feature extraction, their performance is usually slightly below XGBoost. Deep learning models such as CNN and hybrid CNN–LSTM architectures can achieve very high accuracy (97 - 100%) [13, 17], but they demand significantly larger amounts of labeled data and higher computational resources. By contrast, the VMD–XGBoost framework provides a better trade-off between accuracy, efficiency, and interpretability. This is consistent with recent findings where XGBoost has been shown to outperform or match CNN, SVM, and RF on bearing fault diagnosis tasks using CWRU data .

The confusion between ball faults and raceway faults (IR or OR) is minimal, suggesting that the proposed method can effectively capture subtle differences in signal patterns caused by different fault locations. This effectiveness is attributed to the use of both IMF-level and reconstructed-signal features, which provide a comprehensive representation of the vibration signal.

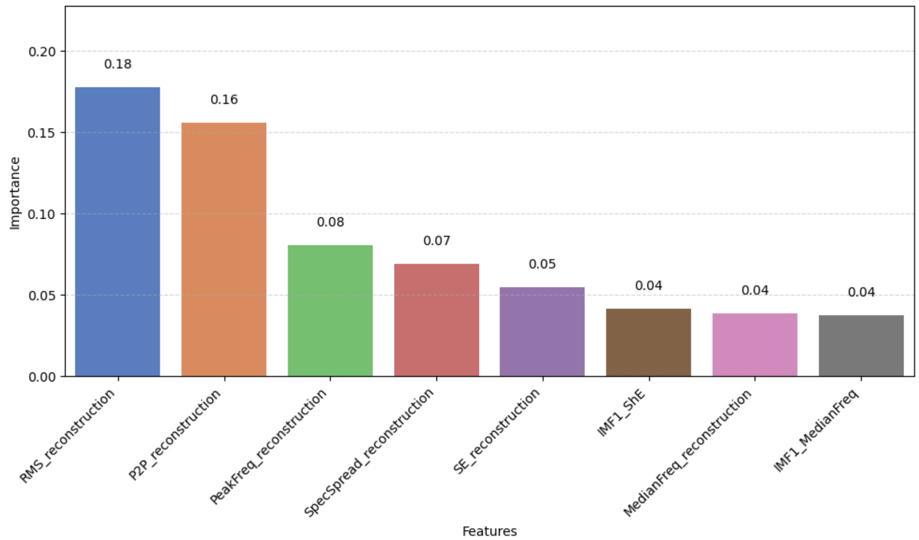

Fig. 7. Top 8 most important features

In addition to high accuracy, the model maintains interpretability through feature importance ranking in XGBoost, allowing insights into which signal components are most indicative of fault types. Figure 7 illustrates the 8 features with the highest feature importances in the XGBoost model. It can be observed that:

- RMS_reconstruction (0.18) and P2P_reconstruction (0.16) are the two most important features, reflecting the overall amplitude variations of the reconstructed signal.
- Frequency-domain features such as PeakFreq_reconstruction (0.08) and SpeSpread_reconstruction (0.07) also play a significant role in identifying fault types characterized by changes in energy spectral distribution.
- Entropy features like SE_reconstruction (0.05) and IMF1_ShE (0.04) provide supplementary information about the signal's complexity, but their contribution is less significant compared to amplitude-based features.

The results indicate that reconstructing the signal from high-energy IMFs significantly improves classification capability. Amplitude and frequency features derived from the reconstructed signal carry stronger diagnostic information compared to those extracted from individual IMFs, as they combine important oscillatory components and reduce the influence of noise. This is substantiated by the high importance of RMS and P2P features in the feature importance plot.

Taken together, the feature importance analysis demonstrates how XGBoost decisions can be directly mapped to established vibration characteristics. Amplitude - based features (RMS, P2P) dominate because they quantify fault severity through energy variations, while frequency- and entropy-based features provide complementary information about spectral shifts and signal irregularity. This layered contribution shows that the classifier does not rely on a single type of feature but integrates multiple perspectives of the signal. Such consistency with domain knowledge strengthens the interpretability of the framework and increases confidence in its diagnostic decisions.

Alongside accuracy and interpretability, the computational efficiency of the framework was evaluated to provide a more comprehensive assessment. The average runtime measurement showed that VMD decomposition and feature extraction required approximately 160.85±16.90 seconds per sample, while XGBoost classification took only 0.789±0.598 miliseconds. With a total processing time of about seconds for each 2048-sample segment (≈42.7 ms signal window), the framework achieves a balance between accuracy and efficiency. These findings confirm that the framework can effectively combine accurate feature construction with rapid classification, ensuring both robustness and responsiveness in the diagnostic process. Overall, the results demonstrate that the method is not only theoretically sound but also computationally feasible, thereby supporting its applicability in practical bearing fault diagnosis and condition monitoring tasks, including scenarios that require timely and reliable decision-making.

Beyond the quantitative results, the superiority of the proposed VMD–XGBoost framework can be attributed to the ensemble learning mechanism of XGBoost. By sequentially training a set of decision trees where each tree corrects the residual errors of its predecessors, the model effectively reduces bias and variance compared to single classifiers such as SVM or Random Forest. This ensures robust performance even under noisy and highly variable operating conditions.

From a practical perspective, this robustness and accuracy are crucial for real-world maintenance systems, where vibration signals are often contaminated by background noise and collected under fluctuating speeds and loads. The ability of XGBoost to not only deliver high classification accuracy but also provide interpretable feature importance strengthens operator confidence and supports actionable decision-making in predictive maintenance. Consequently, the framework can be directly integrated into industrial monitoring pipelines to enable timely fault detection, reduce unplanned downtime, and extend equipment lifespan, thereby contributing to sustainable maintenance practices.

5 Conclusion

The paper presents a powerful and interpretable intelligent fault diagnosis framework. It integrates VMD for feature extraction and XGBoost for classification. The primary objective of this research is also to provide a comprehensive evaluation of intelligent fault diagnosis in rotating machinery, aiming for sustainable manufacturing.

The proposed framework has demonstrated excellent performance, achieving an overall classification accuracy of 98.97% on the widely recognized CWRU bearing fault dataset. This high accuracy is also attributed to VMD's ability to effectively decompose noisy and complex signals, combined with XGBoost's powerful, efficient, and interpretable classification capabilities. The extracted features, particularly from the IMFs, are highly relevant and effective in enhancing the model's discriminative power, enabling accurate identification of different fault types with minimal misclassification.

The findings of this research have significant implications for industrial applications. By enabling timely and accurate fault diagnosis, it helps ensure continuous operation of critical machinery, thereby extending equipment lifespan, reducing maintenance and operational costs (O&M), and minimizing electronic waste. Furthermore, the interpretability of the XGBoost model is a crucial aspect, providing engineers with the necessary trust and insights to design and troubleshoot diagnostic systems in dynamic and varying industrial environments.

To further advance this field, future research could focus on integrating hybrid models that combine advanced machine learning techniques for enhanced fault diagnosis, developing unsupervised or semi-supervised methods to address real-world challenges of limited labeled data, and integrating multi-sensor fusion approaches for a comprehensive view of machine health. Continued contributions in these areas will lead to more robust, precise, and autonomous diagnostic systems, further supporting the resilience and sustainability of industries.

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