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RESEARCH

Comparative Analysis of Machine Learning Techniques for Fault Diagnosis of Rolling Element Bearing with Wear Defects

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A B S T R A C T

Rolling Element Bearings perform a vital function by ensuring the reliable and efficient operation of machinery in modern industries. Timely and accurate diagnosis of bearing faults is essential for preventing unexpected failures and minimizing downtime. This research addresses these challenges by employing advanced signal processing techniques and machine learning algorithms. The study investigates and optimizes fault diagnosis of rolling element bearings using various machine learning techniques, including Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), K-Nearest Neighbors (KNN), and Multi-Layer Perceptron (MLP). The study utilizes naturally occurring defect vibrational data obtained from continuous running in the experimental test rig. Initially, a baseline for fault classification accuracy was established using raw vibration data. Then, Signal-to-Noise Ratio (SNR) was introduced to enhance data quality and alleviate the impact of noise. The model was further refined by extracting 14 types of features from the SNR-enhanced vibration data, presenting a comprehensive depiction of fault patterns and finally, machine learning techniques were applied to categorize faults using the aforementioned datasets, facilitating a comparative analysis of results. This optimization of the signal enhancement methodology significantly improved the fault diagnosis accuracy. As per the result obtained, Random Forest method consistently outperforms when applied to the feature-enhanced SNR dataset. The findings contribute to a more accurate and reliable identification of faults, offering significant advancements in the field of machinery health monitoring and predictive maintenance.

1. INTRODUCTION

Rolling element bearings provide a supportive role for smooth functioning of rotating machines in various industries, including manufacturing, energy, and transportation [1]. Their continuous and reliable performance is essential for maintaining the efficiency and safety of industrial processes. However, these bearings are susceptible to wear and deterioration due to environmental and operational factors, which lead to unexpected failures. Such failures often result in costly downtime, repairs, and safety risks [2]. To mitigate these, condition monitoring of bearings has become crucial in predictive maintenance strategies [3,4].

Effective fault diagnosis of rolling element bearings significantly enhances predictive maintenance programs [5], ensuring early detection and resolution of potential issues before they escalate into more severe problems [6]. Traditional fault detection methods often struggle with data quality issues, leading to inaccurate diagnoses. Addresses the challenges associated with accurately detecting bearing faults, particularly in noisy and complex industrial environments, by applying advanced machine learning techniques combined with preprocessing methods, such as signal-to-noise ratio (SNR) enhancement to improve the accuracy and reliability of fault diagnosis.

In recent years, advancements in sensor technologies and techniques related to processing signals have revolutionized in the field of fault diagnosis for bearings. These innovations have led to the development of advanced methods capable of accurately detecting, classifying, and predicting bearing faults. Various approaches are employed for fault classification. Zheng et al. [7] explored the acoustic emission signals and machine learning techniques for enhanced bearing fault diagnosis, highlighting the synergies between these modalities and reporting promising results. Mohammed and Abdulhady [8] integrated vibrational signal assessment and cumulative sum control charts for condition monitoring. The research successfully demonstrates the effectiveness of this combined approach in accurately detecting faults, providing valuable insights for optimizing maintenance practices and preventing unexpected failures in rolling bearings. Among various methods, the vibration-based approaches are more effective in bearing diagnostics and its potential to improve predictive maintenance strategies through combining with other techniques. Randall and Antoni [9] Presented envelope analysis and spectral kurtosis diagnosis methods for analyzing acceleration signals in the presence of masking signals. Real-life case studies demonstrate the successful application of these techniques, showcasing their effectiveness in identifying bearing faults and separating signals from other machine components. Tong et al. [10] delve into the fusion of multi-sensor data using Dempster–Shafer evidence theory for bearing fault detection, offering a reliable approach with improved diagnosis accuracy. Han et al. [11] introduced a fault diagnosis approach for rolling bearings utilizing multiscale Rényi entropy and AdaBoost ensemble learning, achieving improved accuracy in fault detection. Bin et al. [12] proposed a fault diagnosis methodology based on wavelet packet decomposition and Dempster–Shafer theory, showcasing an integrated approach for improved accuracy. The presence of noise in the vibration signal makes it difficult for the model to accurately classify the fault categories. To address this, some denoising methods are combined with the raw signals to enhance classification accuracy, allowing the model to effectively discern fault categories despite the presence of noise in the vibration data. Abbasion [13] proposed a hybrid method for rolling elements bearing diagnosis of fault, combining wavelet transform and empirical mode decomposition to enhance the diagnosis capabilities. Zhang et al. [14] propose a hybrid method combining variational mode decomposition and ensemble empirical mode decomposition for bearing fault diagnosis. Hamadache M and Lee D. [15] introduced an algorithm that effectively enhances signal-to-noise ratio in incomplete faulty signals. By combining modified principal component analysis with a low-pass filter, it outperforms traditional methods in preserving fault information while reducing noise. Experimental validation on ball bearing fault detection demonstrates its effectiveness. Wei et al. [16] offered a comprehensive examination of various defect detection methods for rolling element bearings, covering both traditional and advanced approaches and summarized comparative effectiveness. Advanced approaches like machine learning techniques have significantly advanced the field of bearing fault diagnosis. These methods increase diagnostic accuracy and efficiency while reducing the reliance on expert knowledge required in traditional methodologies. Singh et al. [17] explored the application of artificial neural network (ANN) for bearing fault detection and classification, presenting a methodology for effective implementation. Samanta [18] investigated the use of decision trees for diagnosis defects in bearings based on vibrational signals, showcasing a data-driven approach achieving an accuracy of 85% based on vibration signal.

The literature assessment revealed that using traditional signal processing techniques alone is insufficient to achieve improved results. Detecting industrial operational surface faults in rolling element bearings from vibration signals with high accuracy in the early stage is one of the major challenges. In order to achieve high accuracy, various signal analysis techniques are explored in this work before feature extraction, and the performance is evaluated with raw signals. Moreover, the usage of SNR in integration with statistical features is considered. Accordingly, the main contributions of this research: the test bearing operated continuously for over 2000 hours to simulate the development of naturally occurring operational surface defects on the bearing surface similar to those found in practical applications and capture vibration signal at three distinct point of lifecycle of bearing. Then signal to noise ratio (SNR) was introduced to improve the quality of vibration signal by reducing noise impact. In the subsequent phase, efficiency was optimized by extracting 14 kinds of features which includes Mean, Max, Min, Peak to peak, Variance, Root Mean Square (RMS), Absolute mean, Shape factor, Impulse factor, Crest factor, Absolute max, Clearance factor, Kurtosis and Skewness, from the SNR-enhanced vibration data. In the final, Random Forest, Support Vector Machine, Logistic Regression, K-Nearest Neighbors, and Multi-Layer Perceptron based machine learning models are implemented and compared for fault classification. These findings offer a critical need in industrial maintenance by developing more accurate and reliable methods for fault diagnosis in rolling element bearings, with applications that greatly benefit a wide range of industries. The methodology flowchart is depicted in Fig. 1.

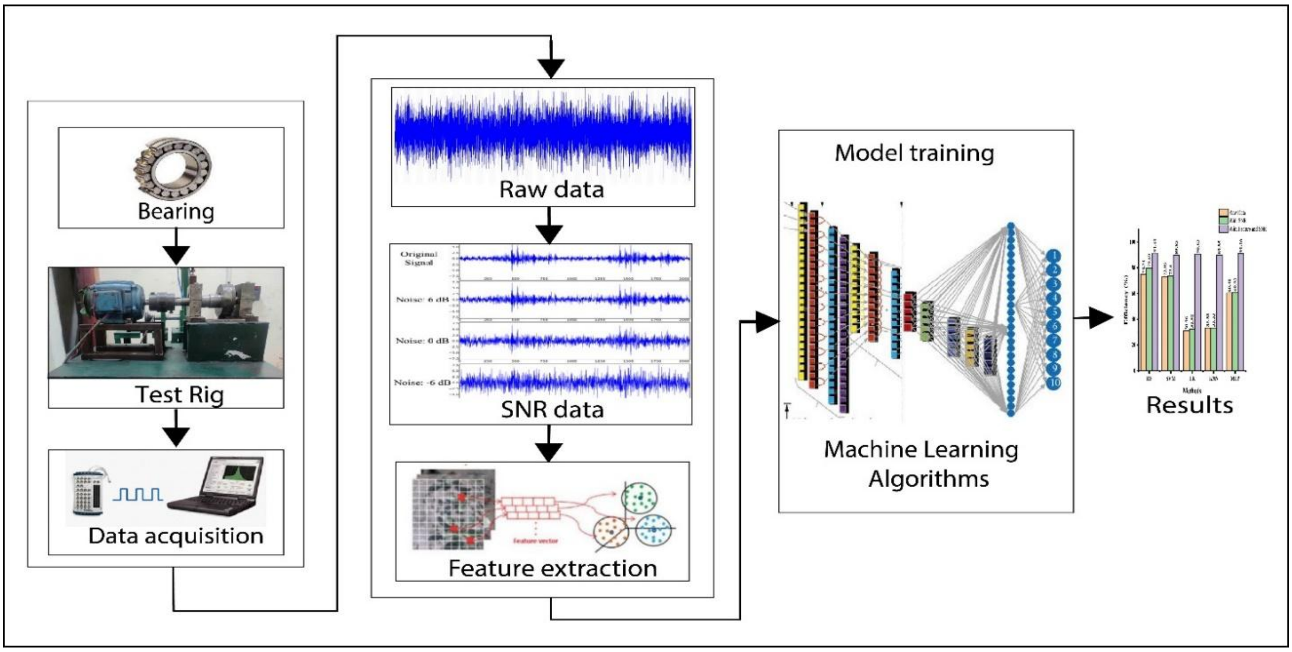


Fig. 1. The structural framework of the proposed fault diagnosis method.

2. SIGNAL TO NOISE RATIO

Signal to Noise Ratio (SNR) is a measure used to quantify the relative strength of a signal against the background noise in a system, with positive and negative values holding different significance. A positive SNR indicates that the signal strength exceeds the noise level, which is desirable for clearer detection and analysis of fault information. A negative SNR means the noise is stronger than the signal, making it difficult to accurately detect or interpret the signal [19]. It is a crucial concept in various fields, including telecommunications, electronics, and signal processing. SNR is typically expressed in decibels (dB) and represents the ratio of the power or amplitude of a signal to the power or amplitude of background noise [20]. The formula for SNR is given in equation 1. A higher SNR value indicates a stronger and more distinguishable signal relative to the noise. It is desirable for clear and reliable communication, accurate measurements, and high-quality signal processing. Conversely, a lower SNR suggests that the signal is weaker and may be more susceptible to interference from noise, increasing the degradation in signal quality. Increasing the SNR is often a goal in the design and optimization of communication systems and electronic devices to ensure accurate and reliable operation.

$$SNR = 10 \times log_{10} \left(\frac{\text{Signal energy}}{\text{Noise energy}} \right) \qquad (1)$$

The aim is to assess the SNR for a given dataset by generating white noise. In signal processing, white noise is a random signal characterized by equal power density across all frequencies. Mathematically, white noise is generated using the Gaussian distribution, with a mean of 0 and a standard deviation of 1. Depicted in equation 2 [20].

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \, exp\left(\frac{(x-\mu)^2}{2\sigma^2} \right) \qquad (2)$$

Where x is the random variable, μ is the mean of the distribution and σ is the standard deviation. This ensures that the resulting noise exhibits randomness without bias towards any particular frequency. The length of the white noise sequence determines the number of random samples generated, providing flexibility in the sample size for analysis. Additionally, clipping the generated noise values to a defined range constrains the noise amplitude. The addition operation is applied element-wise by combining each element of the original dataset with the corresponding element of the generated white noise. This process generates a new dataset by adding intentional noise to the original signal. The resulting dataset is analyzed to evaluate signal processing algorithm performance.

3. FEATURE EXTRACTION

The statistical features were extracted from the SNR-enhanced signals to ensure that all potentially informative characteristics of the vibration signals were represented. These features were selected to capture both time-domain and frequency-domain aspects critical for distinguishing various types of faults.

To optimize this feature set, applied feature importance analysis techniques. This analysis helped identify features that provided minimal predictive value and the most effective features for distinguishing between healthy and faulty bearings. This streamlined feature set effectively captures the essential characteristics of vibration signals necessary for fault diagnosis. The extracted feature includes [21,22]:

3.1 Mean

The mean value represents the average of all data points in the signal.

$$Mean\ (\bar{x}) = \frac{1}{n} \sum_{i=1}^{n} x_i \qquad (3)$$

Where x_i are the data points and N is the total number of data points.

3.2 Maximum (Max)

The maximum value is the highest amplitude in the data set.

$$Maximum = \max(x_i) \qquad (4)$$

3.3 Minimum (Min)

The minimum value is the lowest amplitude in the data set.

$$Minimum = \min(x_i) \qquad (5)$$

3.4 Peak-to-Peak (PP)

The peak-to-peak value represents the range of values in the signal, calculated as the difference between the maximum and minimum values.

$$PP = Maximum - Minimum \qquad (6)$$

3.5 Variance

The variance measures the spread or variability of the signal from its mean.

$$Variance = \frac{1}{n}\sum\nolimits_{i=1}^{n}(x_i - \bar{x})^2 \qquad (7)$$

3.6 Root mean square (RMS)

The RMS value measures the effective power or amplitude of the signal.

$$RMS = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n} x_i} \qquad (8)$$

3.7 Absolute mean

The absolute mean is the mean of the absolute values of the data points.

$$Abs\ Mean = \frac{1}{n}\sum\nolimits_{i=1}^{n}|x_i| \qquad (9)$$

3.8 Shape factor

The shape factor is the ratio of the RMS value to the absolute mean value.

$$SF = \frac{RMS}{\frac{1}{n}\sum_{i=1}^{n}|x_i|} \qquad (10)$$

3.9 Absolute maximum

The absolute maximum is simply the maximum of the absolute values of the signal data points.

$$Abs\ Maximum = \max(|x_i|) \qquad (11)$$

3.10 Impulse factor

The impulse factor is the ratio of the maximum value to the absolute mean value.

$$IF = \frac{Abs\ Maximum}{\frac{1}{n}\sum_{i=1}^{n}|x_i|} \qquad (12)$$

3.11 Crest factor

The crest factor is the ratio of the maximum value to the RMS value.

$$CF = \frac{Abs\ Maximum}{RMS} \qquad (13)$$

3.12 Clearance factor

The clearance factor is the ratio of the maximum value to the square of the RMS value.

$$ClF = \frac{Abs\ Maximum}{(\frac{1}{n}\sum_{i=1}^{n}\sqrt{|x_i|})^2} \qquad (14)$$

3.13 Kurtosis

Kurtosis measures the "tailedness" of the data distribution. Higher kurtosis indicates more outliers.

$$Kurtosis = \frac{\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}}{n}\right)}{\sigma^2} \qquad (15)$$

3.14 Skewness

Skewness measures the asymmetry of the data distribution around the mean.

$$Skewness = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{n} \qquad (16)$$

4. EXPERIMENTATION

Experimental tests were performed on dedicated rig to collect vibration signals from healthy and operational faulty bearings. The setup includes a three-phase 2.3 kW AC motor with a variable frequency drive to control and maintain consistent speed, two bearing SKF 6411 and NJ307ECP. The entire setup mounted on I-section beams secured a concrete block to minimize external vibrations. The experiment took place in an atmospheric environment, and an anechoic chamber was used to reduce external noise interference during the experiment. Fig. 2 illustrates an arrangement of wire rope and pulley system on test rig. A radial load was applied to the load rotor, which is positioned 50 mm from the test bearing. The NJ307ECP test bearing featured an outer diameter of 80 mm, inner diameter of 35 mm, rolling element diameter of 11 mm, and axial width of 21 mm. The experiment replicated real-world conditions by running a bearing continuously in a test rig for 2000 hours at a constant speed of 8000 rpm and a radial load of 1.5 kN. Over time, faults occurs on the bearing surface, closely resembling defects commonly seen in industrial operations.

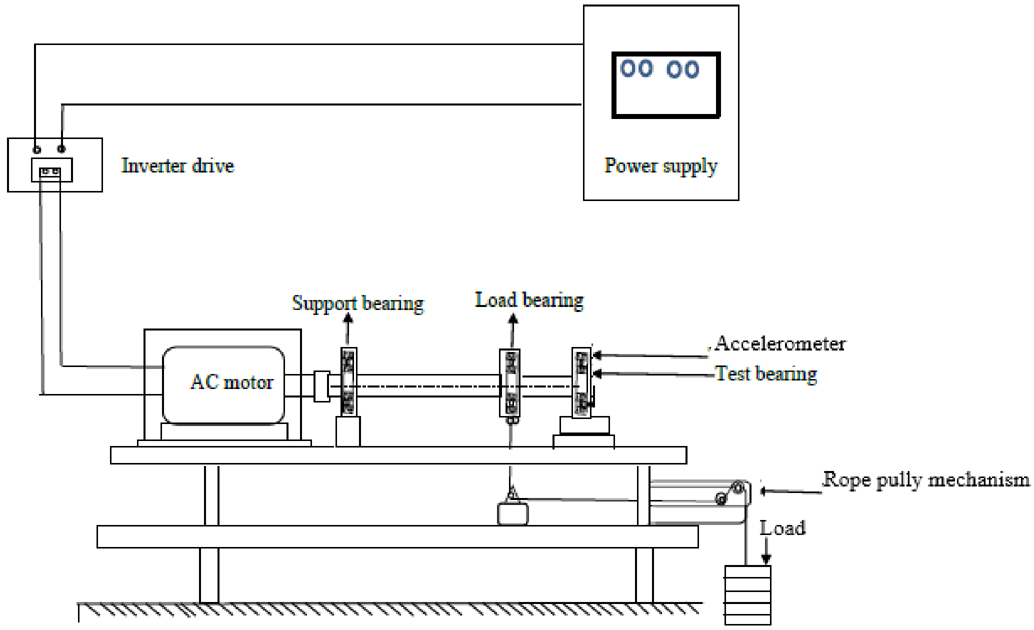


Fig. 2. Schematic diagram of experimental test rig.

The data was collected from an experimental test rig, which was specifically designed to simulate real-world operating conditions of rolling element bearings. Experiments were conducted to run the bearing over 2000 hours at a radial load of 1.5 kN and a constant rotational speed of 8000 rpm in atmospheric conditions. Over a continuous operation of 2000 hours, vibration data was recorded at three critical time points: Zero hours (healthy condition), after 1000 hours of operation (intermediate wear), and after 2000 hours of operation hours (severe wear).

For each time point, a magnetic base accelerometer was used to capture vibration signals, with a sampling frequency of 20 kHz over a period of one second for each sample. The vibration signals were stored using the DEWESoft system on a desktop computer. The dataset included signals from both healthy bearings and bearings with occurring wear defects, which developed progressively during continuous operation. This dataset serves as the basis for the fault diagnosis models applied.

5. CLASSIFICATION METHODS

This research involves fault classification for rolling element bearings using machine-learning models. The datasets used for classification are captured at three distinct time points: initially at zero hours, subsequently after 1000 hours of operation, and finally after 2000 hours of operation. These time points represent various stages in the lifecycle of the rolling element bearings, reflecting the evolution of vibration patterns over time. The software used in this program is Python with Scikit-Learn library. The computer used to run the network is configured with an Intel Core i7 CPU, and 16GB RAM. Integrating this temporal dimension into the dataset enriches the analysis by capturing the bearing behaviour across various operational durations, thereby enabling a comprehensive understanding of fault progression and detection.

The collected raw vibration signal was preprocessed using Signal-to-Noise Ratio (SNR) enhancement to reduce noise and improve signal clarity. After the SNR adjustment, 14 statistical features were extracted from the vibration signals, as described in section 3.

The input data fed into the machine learning models consisted of: Vibration signal samples recorded at three-time intervals (0 hours, 1000 hours, 2000 hours), Preprocessed SNR-enhanced dataset, 14 extracted features for each sample of SNR enhanced dataset, including time-domain and frequency-domain features.

The entire dataset was split into training, testing, and validation sets using random sampling method with a 70:15:15 ratio respectively. This allowed for effective model training while ensuring that the models were tested on unseen data to evaluate generalization performance. Each model was trained using the training dataset and evaluated on the testing and validation datasets to assess classification accuracy. Performance of machine learning models across these datasets to discern their adaptability and efficacy in bearing fault diagnosis. The models are assessed based on their accuracy in classifying the fault pattern in the vibration data. The results indicate the varying strengths of each model under different data conditions, emphasizing the importance of feature engineering and considering SNR in enhancing fault classification accuracy. It validates the effectiveness of models in real-world scenarios, enhancing the theoretical foundation for predictive maintenance strategies. The process of model is shown in fig. 3.

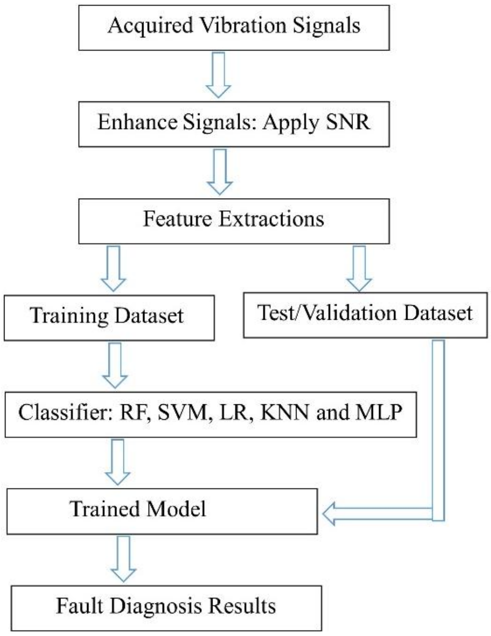


Fig. 3. Flow chart of fault diagnosis models.

5.1 Random forest (RF)

RF is an ensemble learning algorithms renowned for its effectiveness in classification and regression tasks. It builds numerous decision trees in the training process, each trained on a resample of the dataset with feature randomization at each split. The final prediction is determined through a voting mechanism for classification or averaging for regression, leveraging the collective wisdom of diverse trees [23]. This approach reduces overfitting, enhances generalization, and estimates out-of-bag error. The algorithm also assigns importance scores to features, aiding in feature selection, with its capability to manage high-dimensional data, resist overfitting, and parallelize tree construction, Random Forest stands is an accurate and widely utilized machine learning technique. The function of output value is shown in equation 17 [23].

$$\hat{y}_{pred} = \frac{1}{\beta}\sum_{b=1}^{B}\hat{y}_b \tag{17}$$

Where $\hat{y}_b$ is the predicted value from tree b, β is the model coefficient, and $\hat{y}_{pred}$ is the final predicted value. These equations capture the essence of how Random Forest amalgamates the forecasts from numerous decision trees to produce reliable and precise predictions. The power of Random Forest lies in the diversity and randomness introduced during both the training of individual trees and the ensemble prediction process.

An RF classifier was trained with 20 decision trees (estimators = 20) to capture complex relationships in the dataset. The model was initialized with a random seed (random state = 42) to ensure reproducibility. The model was fitted to the data and evaluated using five-fold cross-validation, capturing both individual fold accuracy scores and the mean accuracy as performance indicators. Training took approximately 0.5 sec per sample. The ensemble approach of Random Forest is especially suitable for noisy data, as it reduces variance by averaging the predictions of multiple trees.

5.2 Support vector machine (SVM)

SVM is a supervised machine learning algorithm commonly utilized for identification and regression tasks. Its principal aim is to discover a hyperplane that separates data into distinct classes while maximizing the margin between the classes. [24]. SVM can be capability to manage non-linear decision boundaries by using the kernel size. The decision function in the feature space is shown in equation 18 [24].

$$f(x) = sign\left(\sum_{i=1}^{N}\alpha_i\, y_i K(x_i\,, x) + b\right) \tag{18}$$

Here, N represents the count of support vectors, α is the Lagrange multipliers, y is the labels class, K(xi, x) signifies the kernel function and b is the constant value. SVM is recognized for its proficiency in managing high-dimensional data, resilience in the presence of outliers, and effectiveness in capturing complex relationships through kernel functions. The performance of SVM is significantly influenced by the selection of the kernel and tuning parameters.

SVM used a linear kernel to simplify the model with given the dataset and the tolerance was set to 0.1 to influence the stopping criterion. A random state of 100 (random state =100) was set for reproducibility. The model required 0.6 seconds per sample in computational time, and five-fold cross-validation was applied to assess generalization, with the average score across folds calculated as the performance metric.

5.3 Logistic regression (LR)

Logistic Regression is a foundational machine learning method, widely used for binary classification tasks [25]. Despite its name, it predicts probabilities not regressions, employing the sigmoid function to transform real values to a [0, 1] range.

$$P(y=1)=\frac{1}{1+\exp\left(-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)\right)} \tag{19}$$

Here, $\beta_1, \beta_2 \cdots, \beta_n$ are the slope coefficients corresponding to each predictor variable $X_1, X_2 \cdots \cdots X_n$. The model equation 19 [25] estimates the probability (P) of the positive class, trained by optimizing coefficients for maximum likelihood, Logistic Regression excels when the relationship between features and the target is approximately linear. Its simplicity, efficiency, and interpretability make it valuable in fields like social sciences, finance, and medicine for binary classification problems.

LR was employed with the Limited-memory BFGS (lbfgs) optimization algorithm, suited for multiclass classification problems (multi class = multinomial). A random seed of 6 was used to enable reproducibility. The model required 0.8 seconds per sample in computational time and underwent five-fold cross-validation to determine its performance, with the mean accuracy across folds was computed to measure model effectiveness.

5.4 K-Nearest neighbors (KNN)

KNN is a versatile machine-learning algorithm applied to both identification and regression tasks. It anticipates the class or value of a data-point by considering the majority class or average of its k-nearest neighbors in the feature space. In classification, it assigns a class label by taking into account the labels of the KNN, while in regression, it predicts a continuous value based on their average [26]. The parameter K is crucial, impacting the trade-off between noise and smoothing. KNN is non-parametric, not presuming any assumptions about the distribution of the data, suitable for complex relationships. Its performance depends on the choice of distance metric and is sensitive to the course of dimensionality. Despite this, KNN remains popular for its simplicity and effectiveness in applications like pattern recognition, image analysis, and recommendation systems.

The KNN classifier was trained with 75 neighbors (neighbors = 75) to account for the complexity and noise in the data. The model required 0.6 seconds per sample in computational time and Five-fold cross-validation was applied to assess the effectiveness of the model, with the mean accuracy score taken as the performance metric.

5.5 Multilayer perceptron (MLP)

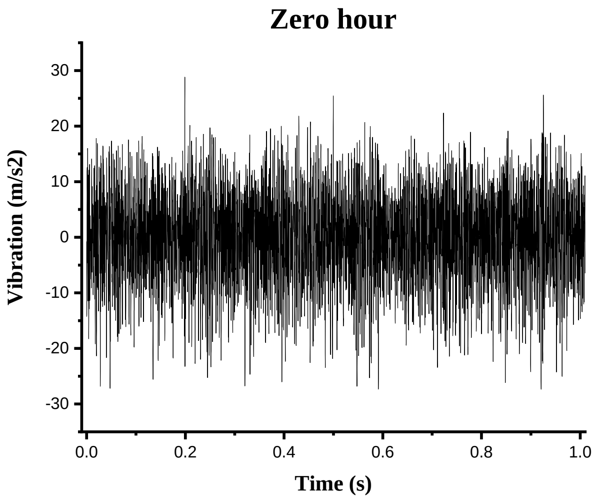
MLP is a neural network model employed in machine learning for both identification and regression tasks, comprising multiple layers of interconnected nodes [27]. MLP processes information through forward and backward propagation. Each node employs an activation function to process the weighted sum of its inputs, enhancing the model's ability to capture complex patterns. MLP's design encompasses an input layer, one or more hidden layers, and an output layer. With the capacity to learn intricate relationships, MLP excels in diverse applications. These include natural language processing, image recognition, and financial forecasting, rendering it a versatile and powerful tool within the domain of artificial intelligence [28].

A Multi-Layer Perceptron classifier was trained with a hidden layer containing 512 units and the Limited-memory BFGS solver for optimization. The regularization parameter was set 10-5 to prevent overfitting. The model was initialized with a random seed 10 to ensure reproducibility and evaluated with five-fold cross-validation with mean accuracy. Computational time required for the model was approximately 15 seconds per sample.

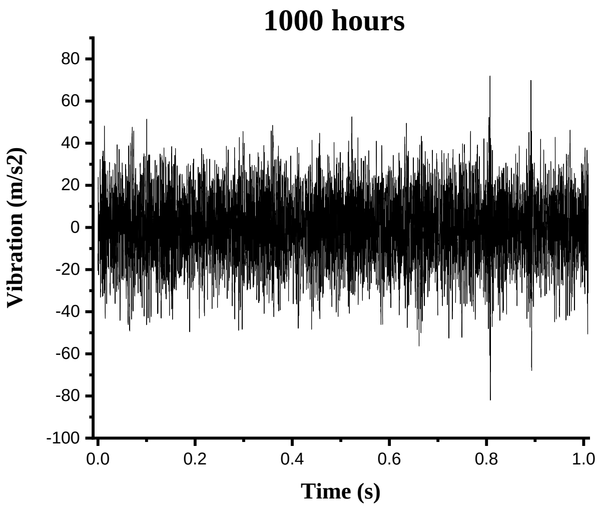
6. RESULTS AND DISCUSSION

This section represents brief summary of outcomes in rolling element bearings subjected under various conditions on a test rig. The bearing underwent continuous operation until a naturally occurring surface defect developed in one of its components. The preliminary indication of an anomaly emerged after 306 hours of continuous operation during the experiment.

Experimental vibrational signal was systematically collected at different intervals, captured the vibrational signal for a healthy bearing, after 1000 hours of continuous operation, and after 2000 hours of continuous operation, visually represented in fig. 4. These vibrational datasets served as crucial indicators to analyze the evolving conditions of the bearing over time, providing valuable insights into its operational health and potential faults.



(a)



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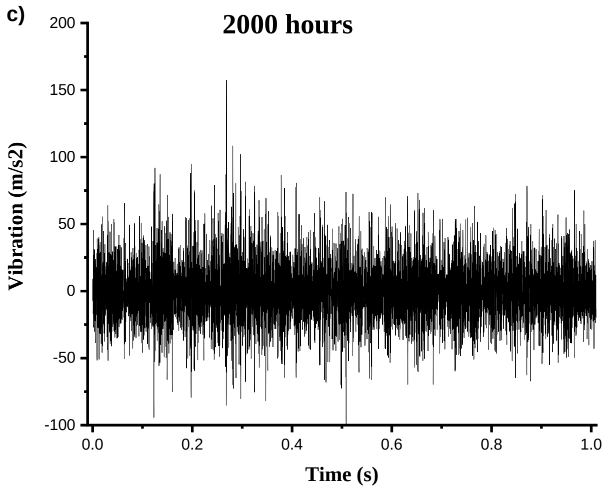

(c)

Fig. 4. Experimental vibrational signals (a) healthy bearing, (b) after 1000 hours of running, (c) after 2000 hours of running.

The dataset, comprising 384 samples across three distinct time intervals (healthy, after 1000 hours and after 2000 hours of defects), enabled the machine learning models to differentiate between different fault conditions. The effectiveness of the results, particularly the high accuracy of the machine learning model, will be attributed to the diverse and comprehensive nature of the dataset or data pool, which captured progressive fault development in a controlled environment. The overview of the dataset, including the number of samples at the different conditions, is shown in Table 1.

Table 1. Data summary.

Bearing Condition	Number of Samples	Vibration Signal Characteristics
Healthy Bearing (Zero hour)	128	Baseline vibration, low amplitude
After 1000 hours of operation	128	Moderate amplitude
After 2000 hours of operation	128	High amplitude, irregularities
Total	**384**	

The performance of the obtained signal was evaluated using five different machine learning models: Support Vector Machine, Random Forest, Logistic Regression, K-Nearest Neighbors, and Multi-layer perceptron. In the initial phase of fault classification approach, raw vibration data was used to establish a baseline for fault classification accuracy. The maximum accuracy obtained for the above mentioned model is 74.74%, which is comparatively lower than the existing method. Further, for recognizing the potential improvement, SNR is applied to the raw vibration signals to mitigate the effects of noise. This is achieved by adjusting the SNR values to ensure that the informative signal components (related to bearing faults) stand out more clearly against the background noise. Specifically, the SNR values are tuned between 19 dB and 45 dB. This range allows for an optimal balance between eliminating noise and retaining essential signal characteristics. The raw data undergoes transformation where Gaussian white noise is added based on a predefined SNR value, which is calculated using Equation (1). This improved dataset was then further analysed using the above mentioned machine learning models. Among these, Random Forest exhibited the highest accuracy when the SNR value was 26dB. Lower SNRs left noise, hindering fault detection, while higher SNRs over-smoothed the data, losing crucial fault information. The 26dB level balanced noise reduction and signal preservation, supporting accurate fault classification. It also observed that there is a slight improvement in the accuracy to the original vibration signal, highlighting the algorithm's resilience and effectiveness in noise-prone conditions.

In the subsequent phase, the efficiency of the fault classification system was further optimized by extracting 14 kinds of relevant features from the SNR-enhanced vibration data. These features were carefully selected to capture crucial aspects of the system's behavior, providing a more comprehensive and informative representation of the underlying fault patterns.

The final step applied machine learning models to classify faults based on the enriched dataset containing both SNR-enhanced signals and the extracted features. By combining these strategies, our approach is not only to mitigate the influence of noise but also to leverage the distinctive characteristics captured through feature extraction. This multistep process was designed to synergistically improve the overall accuracy and efficiency of fault identification, enabling more accurate and reliable identification of faults in the system. Table 2 illustrates the performance of machine learning algorithms across different datasets.

Table 2. Results obtained for various datasets.

	Random Forest	**Support Vector Machine**	**Logistic Regression**	**K-Nearest Neighbors**	**Multi-Layer Perceptron**
Raw Data	74.74	73.05	30.96	33.33	60.41
With SNR	79.69	73.60	32.52	33.33	60.93
With SNR-featured	91.41	89.85	90.63	89.85	91.16

In the initial assessment using raw vibration data, the machine learning models displayed varying accuracies 74.74% for Random Forest, 73.05% for Support Vector Machine, 30.96% for Logistic Regression, 33.33% for K-Nearest Neighbors, and 60.41% for Multi-Layer Perceptron, respectively. Upon adding SNR to the dataset, an improvement was observed. Random Forest's accuracy increased to 79.69%, and Logistic Regression exhibited a modest increase to 32.52%, while K-Nearest Neighbors remained consistent at 33.33%. Multi-layer Perceptron and Support Vector Machine showed a slight improvement to 60.93% and 73.60%, respectively. After the introducing SNR along with features further improved performance, with Random Forest leading at 91.41%, followed closely by Support Vector Machine, Logistic Regression, K-Nearest Neighbors, and Multi-Layer Perceptron at 89.85%, 90.63%, 89.85%, and 91.16%, respectively. The comparison results are shown in fig. 5. The results indicated that models with raw data exhibited higher lack of fit values, reflecting the challenges of noise and unprocessed data. After introducing SNR enhancement and feature extraction, the lack of fit values significantly decreased, indicating a better fit of the models to the processed data. These indicate the varying strengths of each model under different data conditions, emphasizing the importance of feature engineering and considering SNR in enhancing fault classification accuracy.

The effectiveness of these techniques varies with the SNR ratio applied in the raw signal. SNR focuses on improving data quality by reducing noise and feature extraction offers a more detailed and informative representation of fault patterns, minimizing the lack of fit and improving overall performance. The accuracies of all mentioned machine learning techniques have reached approximately 90% for the SNR-featured dataset.

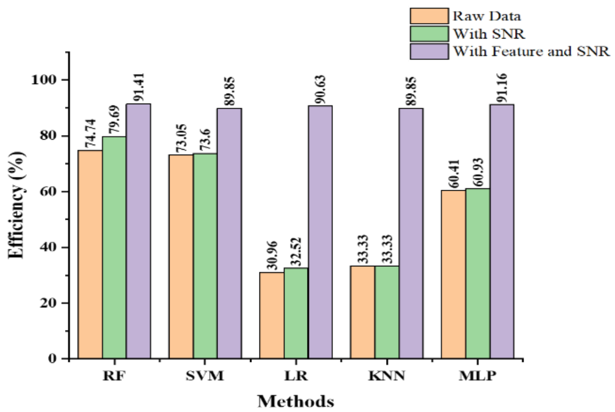

Fig. 5. Comparative results of machine learning method across various dataset.

Evaluating the contribution of individual features to classification accuracy involved calculating feature importance scores using the Random Forest algorithm. These scores indicate the relative significance of each feature in determining fault classification, shown in fig. 6. Analysis indicated that Root Mean Square (RMS), Variance, and Maximum were the most effective features for distinguishing between healthy and faulty bearings, whereas Shape Factor, Kurtosis, and Mean had comparatively lower contributions to classification performance.

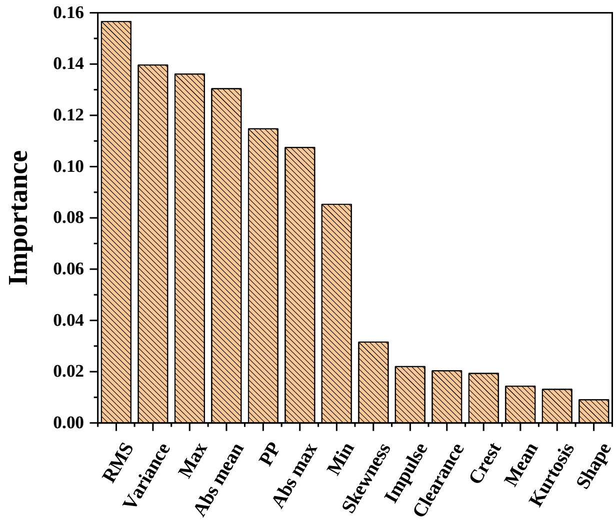

Fig. 6. Feature mapping.

The methodology highlights the adaptability and effectiveness of various machine learning models under different data conditions, showcasing their potential in fault diagnosis. The findings provide valuable insights for industrial applications, offering a practical framework for implementing advanced machine learning techniques in predictive maintenance strategies, which lead to improved operational efficiency and detect failure before downtime. Furthermore, the research contributes to the existing body of knowledge by emphasizing the importance of data quality and feature engineering in machine learning applications, paving the way for future research in fault diagnosis and condition monitoring.

Table 3. Classification accuracy of the proposed model in comparison to previous studies.

Proposed/Existing work	Features	Measured signal	Classifier	Accuracy (%)
Kankar et al. [29]	Statistical feature	Vibration signal	ANN & SVM	80 & 85
Kumar et al. [30]	Continuous wavelet transform	Vibration signal	KNN	83.3
Pan et al. [31]	Linear kernel	Vibration signal	TCA	84.51
Present work	SNR with Statistical feature	Vibration signal	RF	91.41

Table 3 summarizes a comparison study between the proposed method and existing published works. It is observed that the performance of the proposed method is better than the other existing methods. The proposed model achieved 91.41% classification accuracy. This improvement boosts operational reliability by enabling earlier fault detection, which can prevent failures and reduce downtime in industrial applications. It also sets a new benchmark, demonstrating the effectiveness of combining Signal-to-Noise Ratio (SNR) enhancement with machine learning techniques.

7. CONCLUSIONS

The evaluation of fault classification performance for rolling element bearings entailed a thorough analysis of five machine learning models, Random Forest, Support Vector Machine, Logistic Regression, K-Nearest Neighbors, and Multi-layer Perceptron. Each model underwent scrutiny at distinct data processing stages to discern their adaptability and efficacy in bearing fault diagnosis. Initially, with raw vibration data, Random Forest emerged as the leading performer with an accuracy of 74.74%. The subsequent integration of SNR demonstrated a consistent enhancement in model accuracy, with Random Forest leading at 79.69%. The most significant advancement was observed after incorporating additional feature extraction into the SNR dataset. In this final stage, Random Forest, Logistic Regression, and Multi-Layer Perceptron exhibited exceptional accuracy, reaching above 90%, emphasizing the substantial impact of feature and SNR in refining the fault classification capabilities of these machine learning models. These comprehensive findings recommend Random Forest for fault diagnosis in industrial settings due to its high accuracy and quick prediction capabilities, integrating Random Forest into predictive maintenance systems ensures reliable, efficient, and scalable solutions for effective machinery fault diagnosis. Future research may explore the integration of deep learning techniques to further enhance the accuracy and automation of bearing fault diagnosis.

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