Multi-Source Information Fusion Fault Diagnosis for Rotating Machinery using Signal and Data Processing

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Abstract
Machine fault diagnosis is crucial in industrial systems to enhance reliability, lifetime, and service availability. Intelligent fault diagnosis (IFD) using artificial intelligence (AI) techniques has emerged as a promising approach for automating machine health assessment and reducing labor costs. One approach to improve fault diagnosis accuracy, which has become a highly relevant research topic, is to use multi-data fusion, which combines information from multiple sources to make a more informed decision. However, there is a lack of research focusing on the detection of combined machinery faults from multiple sensors. Indeed, when combined (and emerging) faults happen in different parts of the rotating machines their features are deeply dependent and the separation of characteristics becomes complex, while multi-sensor information can provide more comprehensive fault features to deal with the diagnosis and identification of multiple combined faults. This paper presents a comprehensive methodology for diagnosing combined faults using data fusion and machine learning techniques. The proposed approach leverages multiple types of sensor data, including vibration, current, temperature, and acoustic data, sensors to provide a comprehensive picture of the machine's health. Our proposed methodology incorporates an ensemble learning approach and time-domain features to improve diagnostic accuracy. The proposed approach is tested on a publicly available dataset of rotating machinery with multiple faults. The results indicate that the method is viable and achieves good accuracy and efficiency.

1 Introduction

Rotating machinery plays a crucial role in modern industries, including manufacturing, transportation, and power generation. The efficient operation of these machines is vital to ensure the continuity of industrial processes and the safety of workers. However, rotating machinery is prone to various types of faults that can result in unexpected downtime, production losses, and safety hazards. Therefore, timely and accurate diagnosis of machinery faults is essential to reduce maintenance costs and ensure the reliability and availability of machines. Diagnostic is typically a reactive action performed after a fault or problem has already occurred. The purpose of fault diagnostic is to identify the cause of the problem or fault so that it can be addressed and resolved [1].

In recent years, Intelligent Fault Diagnosis (IFD) has emerged as a promising approach to improve the accuracy and efficiency of machinery fault diagnosis. Several studies have explored the applications of Artificial Intelligence (AI) techniques such as machine learning, pattern recognition, and signal processing, in machine fault diagnosis, highlighting its potential for enhancing diagnostic accuracy and enabling automated fault recognition. Notably, Y. Lei et al. [2] conducted a comprehensive review and roadmap of machine learning applications in machine fault diagnosis, providing valuable insights into the current state of the field and outlining future research directions. R. Liu et al. [3] also conducted a noteworthy review on the use of artificial intelligence for fault diagnosis of rotating machinery. Their review focused specifically on the application of artificial intelligence techniques, including machine learning, in diagnosing faults in rotating machinery. These reviews collectively underscore the growing interest in applying artificial intelligence techniques to fault diagnosis in rotating machinery. By leveraging the insights gained from these seminal reviews, this paper contributes to the existing body of knowledge by presenting a comprehensive methodology for diagnosing combined faults in rotating machinery using data fusion and signal processing techniques.

While IFD has shown significant success in detecting single faults in rotating machinery, diagnosing combined faults remains a challenging problem. Combined faults occur when multiple faults occur simultaneously or sequentially in different parts of the machine, and their features are deeply interdependent [1], making them difficult to separate and identify. Therefore, detecting combined faults requires integrating information from multiple sources and fusing it to extract more comprehensive fault features. Multi-source information fusion is a promising technique for diagnosing combined faults in rotating machinery, it involves combining data from multiple sensors, such as vibration, current, temperature, and acoustic sensors, to improve the accuracy and robustness of fault diagnosis. Therefore, combining machine learning and deep learning with multi-source information fusion techniques can further improve the accuracy and reliability of machinery fault diagnosis, providing significant benefits to the industry.

This article presents a comprehensive methodology for diagnosing combined faults using data fusion and machine learning algorithms. The methodology involves data acquisition, data pre-processing including direct data fusion, and feature extraction. To perform the classification of faults, we use machine learning algorithms such as Logistic Regression, k-Nearest Neighbor (kNN), and Gaussian Naïve Bayes, which are trained on the extracted features. Finally, we combine the different decisions obtained from the different algorithms using stacking ensemble learning technique to increase the overall accuracy of the diagnosis. The proposed approach is applied to a publicly available dataset to evaluate its effectiveness in diagnosing combined faults. The results indicate that the method is viable and achieves a good level of accuracy and efficiency. The paper also discusses the challenges and limitations of data fusion techniques for intelligent fault diagnosis, while highlighting potential areas for improvement and suggesting future research directions.

2 Related Works

Fault diagnosis in rotating machinery is crucial for ensuring reliable industrial operation. However, diagnosing combined faults, where multiple faults occur simultaneously or sequentially in different machine parts, presents unique challenges. To address these challenges, data fusion techniques have gained significance. Data fusion combines information from multiple sensors to provide a comprehensive understanding of machine health. This subsection explores notable works in data fusion techniques for fault diagnosis in rotating machinery, showcasing advancements in addressing the complexities of diagnosing combined faults.

2.1 Data Fusion Techniques

Multi-source information fusion, also known as multi-sensor fusion or information fusion, is a concept that originated in the mid-1980s and was initially developed for military applications. The Joint Directors of Laboratories (JDL) model proposed by the US Department of Defense Data Fusion Joint Command Lab [4] [5], which is considered the first fusion model in the field of data fusion, provides a framework for understanding the process of information fusion. The JDL model involves detecting, combining, and estimating multi-source data to improve the estimation accuracy, assess the situation, and evaluate information completeness and importance, enabling the extraction of meaningful insights and the generation of reliable results. Based on the abstraction level of data fusion, the process of information fusion can be divided into three levels [6]: data fusion, feature fusion, and decision fusion. At the data fusion level, raw sensor measurements or observations from multiple sources are combined to form a more comprehensive dataset. Feature fusion involves the integration of extracted features from individual sensor data, where relevant characteristics are combined to form a more informative representation of the underlying phenomena. Finally, decision fusion focuses on combining the decisions or outputs from multiple information sources to arrive at a final decision or inference. Within the domain of fault diagnosis for rotating machinery, several studies have investigated the application of data fusion techniques at these different levels.

Some studies in fault diagnosis of rotating machinery have explored the fusion of vibration and acoustic data. For instance, M. Khazaee et al. [7] proposed a feature-level fusion approach using wavelet transform and artificial neural networks for fault diagnosis of a planetary gearbox. R.S. Gunerkar et al. [8] focused on the classification of ball bearing faults using vibro-acoustic sensor data fusion. The authors employed time-domain features. Furthermore, principal component analysis (PCA) was utilized to select the most suitable features from the feature set. You He et al. [9] developed a deep multi-signal fusion adversarial model based on transfer learning and residual network for axial piston pump fault diagnosis, where vibration and acoustic data were fused. The study specifically emphasized the significant benefits of utilizing deep learning techniques, including the application of a residual neural network. These studies demonstrate the effectiveness of integrating vibration and acoustic data to improve fault diagnosis accuracy in rotating machinery.

In addition to vibration and acoustic data fusion, researchers have explored the fusion of vibration and current data for fault diagnosis in rotating machinery. J. Cui et al. [10] proposed M2FN, an end-to-end multi-task and multi-sensor fusion network for intelligent fault diagnosis. They demonstrated the effectiveness of fusing vibration and current data in accurately identifying and classifying faults. S. Liu et al. [11] employed a feature-level fusion approach in their study, the objective of this fusion was to enhance the fault diagnosis process and improve the accuracy of the results.

Researchers have also explored the fusion of a single type of signal for improved diagnostic performance. For example, when considering vibration signals, J. Mi et al. [12] proposed a decision-level fusion method based on evidence theory, integrating multiple sources of vibration data. Similarly, S. Li [13] introduced an ensemble deep convolutional neural network (CNN) model with improved Dempster–Shafer theory evidence fusion for bearing fault diagnosis, specifically fusing vibration signals using the D-S evidence theory to enhance fault classification accuracy and address limitations of single-model-based diagnosis.

Alternatively, in the realm of current signal analysis, specifically using motor current signature analysis (MCSA), M. Azamfar et al. [14] proposed a data-level multi-sensor fusion approach for gearbox fault diagnosis. The study utilized a CNN-based fusion approach combined with the MCSA to improve accuracy in identifying and classifying gearbox faults.

2.2 Combined Faults

Diagnosing combined faults in rotating machinery poses significant challenges due to the complexity and interaction of multiple fault types. Researchers have made notable progress in developing methodologies to address these challenges. M.Y. Asr et al. [1] used a Non-Naive Bayesian Classifier to successfully identify gear and bearing failures. U.I. Inyang et al. [15] proposed a comprehensive learning approach using vibration data to diagnose single and multiple faults across diverse rotating machine components (gearbox, bearing, and shaft). M. Islam et al. [16] proposed a reliable multiple combined fault diagnosis scheme for bearings based on acoustic signals, utilizing heterogeneous feature models and an improved one-against-all multiclass support vector machines classifier. A. Garcia-Perez et al. [17] proposed a condition-monitoring strategy that combines vibration and current data for accurate identification of single or multiple combined faults in induction motors, including broken bar (BRB), outer race damaged bearing (BD), and unbalanced pulley (UNB).

In conclusion, while various studies have investigated data fusion techniques for fault diagnosis in rotating machinery, there is still a lack of research on large-scale sensor fusion, particularly in the context of determining combined faults in different parts of the machinery such as bearings, gears, shafts, rotors, and stators. The existing literature has primarily focused on the fusion of vibration and acoustic data, as well as the fusion of vibration and current data. However, there is a need for more comprehensive and integrated approaches that encompass a wider range of sensor inputs and address the challenges associated with diagnosing complex and combined faults in various components of rotating machinery. Future research efforts should aim to develop novel data fusion methodologies that can effectively handle multiple sensor inputs and provide accurate and reliable fault diagnosis in diverse operating conditions and fault scenarios.

3 Proposed Methodology

In this section, we present the methodology employed for diagnosing combined faults in rotating machinery. The methodology, illustrated in Figure 1, provides a comprehensive framework for the fault diagnosis process. The methodology encompasses data acquisition using multiple sensors, data preprocessing techniques such as data-level fusion and feature extraction, model training, and decision-making using machine learning and ensemble learning. By following this systematic approach, we aim to achieve accurate and reliable fault diagnosis for combined faults in rotating machinery

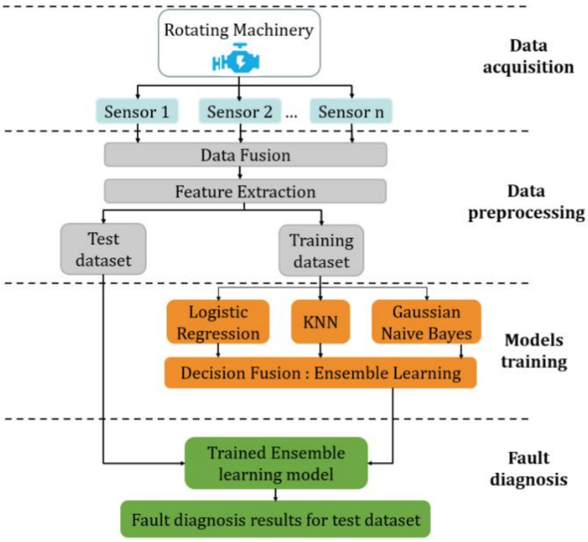

Figure 1: Flowchart of the proposed combined fault diagnosis method

3.1 Data Acquisition Using Multiple Sensors

In this step, data is acquired from multiple sensors installed on the rotating machinery. These sensors can include vibration sensors, acoustic sensors, current sensors, temperature sensors, or any other relevant sensors depending on the specific application. The purpose of using multiple sensors is to capture different aspects of the machine's behavior and enable comprehensive fault diagnosis.

3.2 Data Preprocessing

At this point, the methodology employs data-level fusion to bring together information obtained by different sensors for a more holistic understanding of the machine's health status. This step plays an instrumental role in capturing complementary sensing information from every source and aids in the enhancement of overall equipment insights. Then come to the feature extraction techniques aimed at extracting meaningful attributes from this fused data set based on time-domain analysis, frequency-domain analysis, and other relevant methods available. The objective is to identify relevant characteristics that can tell apart different fault conditions by comparing and analyzing appropriate features extracted from diverse domains.

3.3 Model Training and Fault Classification

An ensemble machine learning model for fault diagnosis uses pre-processed data as input. Firstly, the base-level classifiers, including Logistic Regression, K-Nearest Neighbors (KNN), and Gaussian Naive Bayes, are trained individually using labeled training data. Secondly, the trained base-level classifiers are combined using stacking ensemble learning, which involves training a meta-classifier, specifically Support Vector Machines (SVM) is used in the case of this study, on the predictions made by the base-level classifiers.

3.3.1 Logistic Regression

Logistic regression is a simple and efficient method for binary and linear classification problems [18]. It serves as a linear classifier that models the relationship between input features and class probabilities. By applying a logistic function to a linear combination of the input features, logistic regression estimates the probability of a data instance belonging to a specific class. The logistic function, represented by Equation (1), calculates the probability:

$$Prob(event) = P(X) = \frac{1}{1 + e^{-g(X)}} = \frac{e^{g(X)}}{1 + e^{g(X)}} \tag{1}$$

Where P(X) refers to the probability of a particular event or outcome occurring given a set of input features $X = (x_1, x_2, \dots, x_k)$, and g(X) represents the logit model. The logit model, as shown in Equation (2), transforms the linear combination of input features and their coefficients into the log-odds or logit value:

$$g(X) = \log\left(\frac{P(X)}{1 - P(X)}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k \tag{2}$$

Here $\alpha, \beta_1, \beta_2 \dots \beta_k$, are the regression coefficients estimated using maximum likelihood estimation.

3.3.2 k-Nearest Neighbors (kNN)

k-Nearest Neighbors (KNN) is a popular machine learning algorithm used in various fields, including fault diagnosis in rotating machinery [19] . It is a non-parametric algorithm belonging to the category of instance-based learning [20]. KNN is a simple and supervised machine learning algorithm, capable of solving both classification and regression problems [21]. The algorithm works by measuring the distance between a test sample and the labeled training samples in the feature space. The KNN algorithm then assigns the test sample to the majority class among its K nearest neighbors. The choice of K, the number of nearest neighbors, is a hyperparameter that can be tuned to optimize the algorithm's performance.

3.3.3 Gaussian Naive Bayes

Gaussian Naive Bayes classification is a variant of the Naive Bayes algorithm that assumes a Gaussian distribution for the continuous feature values given the class label [22]. It utilizes Bayes' theorem to calculate the probability of observing a specific value in a feature, given the class label. Each feature is characterized by its mean (μ_y) and variance (${\sigma_y}^2$) within a specific class label (y). The probability of observing a specific value (x_i) in the i^{th} feature, given the class label y, is computed using the normal distribution equation:

$$P(x_i|y) = \frac{1}{\sqrt{2\pi{\sigma_y}^2}} e^{-\frac{(x_i - \mu_y)^2}{2{\sigma_y}^2}} \tag{3}$$

This equation represents the probability density function (PDF) of the normal distribution.

3.3.4 Stacking Ensemble Learning Classifier

In ensemble learning, stacking is a popular technique that combines multiple base-level classifiers to create a meta-classifier that yields improved predictive performance [23]. Each base classifier makes predictions on the input data, which are then combined using a meta-classifier to generate the final prediction. In the context of this work each base classifier, including Logistic Regression, KNN, and Gaussian Naive Bayes, is individually trained using labeled training data. These algorithms learn the relationships between the input features and the corresponding fault labels, enabling them to make predictions on unseen data.

In this approach the meta-classifier Support Vector Machines (SVM) algorithm, is trained to take the predictions from the base classifiers as input features and learn to make the final decision. The stacking ensemble model leverages the collective knowledge of the base classifiers to improve the overall fault diagnosis performance by aggregating their predictions.

3.4 Fault Diagnosis Results For Test Dataset

The trained models make predictions on the test data, classifying the fault conditions present in the rotating machinery. The fault diagnosis results are evaluated based on predefined performance metrics, such as accuracy, precision, recall, and F1-score to assess the effectiveness of the methodology in accurately identifying combined faults.

4 Results and Discussion

4.1 Experimental Setup

The CWRU dataset from Case Western Reserve University Laboratory includes vibration data collected from multiple accelerometers placed around a bearing motor. the experimental setup used for data acquisition of rolling bearings from the CWRU dataset is illustrated in Figure 2. The dataset replicates actual bearing failures caused by electric sparks and encompasses various operating conditions. Faulty bearings with known fault depths (0.007 inch, 0.014 inch, or 0.021 inch) are included, and accelerometers are positioned at the drive end (DE), fan end (FE), and base (BA) of the motor. Time series data is available at sampling frequencies of 12k or 48k, capturing different load types and motor speeds.

In this work, we only consider data acquired at 48 kHz sampling frequency, 1 horsepower external load, and with 1772 rpm speed value. The faults under consideration are located at the drive end, specifically the inner race, outer race and ball fault. To simulate the case of diagnosing multiple faults, we consider a total of 10 fault classes at the drive end bearing. The vibration signals captured from the DE bearing given in Figure 3 showcase the normal healthy condition versus the inner race fault with different fault depths. Although the dataset used in this study lacks multi-source data fusion, it enables the evaluation of the proposed methodology for combined faults by considering multiple fault classes within the vibration data alone.

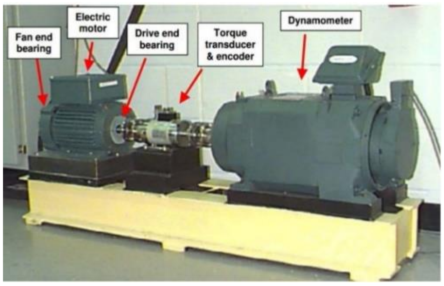

Figure 3: Experimental setup of the bearing motor of the CWRU Dataset

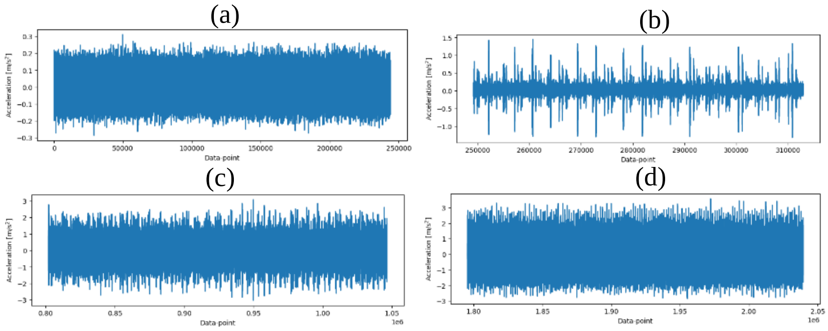

Figure 2: Row vibration signals (a) healthy condition, (b) Inner Race (IR) fault 0.014 inch, (c) IR 0.021 inch (d) IR 0.007 inch

4.2 Performance Assessment of the Suggested Methodology

Based on Figure 3, it is challenging to discern the distinctions between different faults, making diagnosis difficult. Consequently, it is necessary to extract relevant features from the raw signals to facilitate accurate classification. A total of 9 time domain features including statistical ones have been extracted in our analysis. These features encompass maximum value, minimum value, mean value, standard deviation, root mean square value (RMS), skewness, kurtosis, crest factor, and form factor. Detailed information regarding the data splitting and different fault classes can be found in Table 1.

Fault type	Fault size/inch	Label	Test dataset size	Training dataset size
Ball fault	0.007	C1	75	155
	0.014	C2	75	155
	0.021	C3	75	155
Inner race	0.007	C4	75	155
	0.014	C5	75	155
	0.021	C6	75	155
Normal	-	C7	75	155
Outer race	0.007	C8	75	155
	0.014	C9	75	155
	0.021	C10	75	155

Table 1: Information about the experimental dataset taken from CWRU's data

Algorithm	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.942	0.94	0.94	0.94
KNN	0.932	0.93	0.93	0.93
Gaussian Naïve Bayes	0.924	0.93	0.92	0.92
Stacking Classifier	0.972	0.97	0.97	0.97

Table 2: Comparative analysis of various trained algorithms

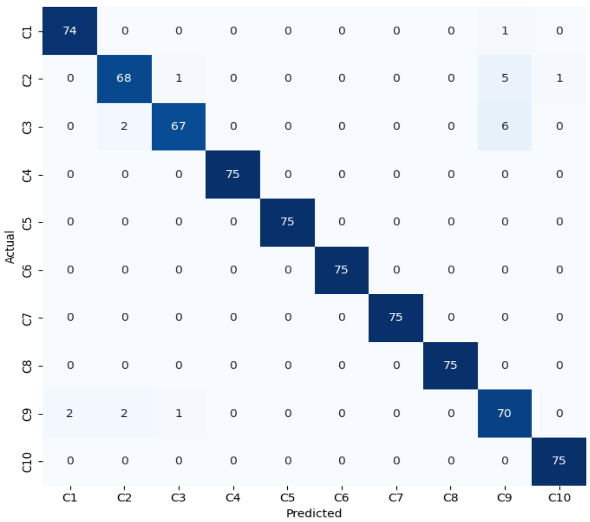

Figure 5: Confusion matrix of the stacking classifier on testing dataset

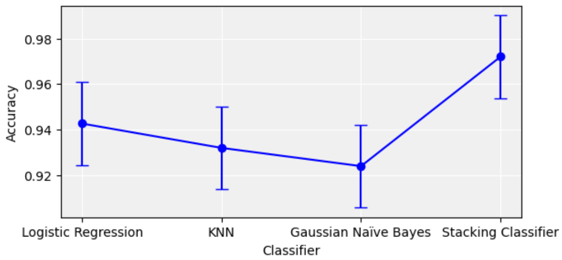

Figure 4: Bar plot comparing classifier accuracy: a visual analysis

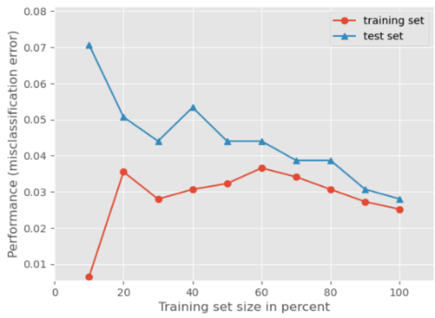

Figure 6: Learning curves of the stacking classifier

The study employed a methodology for diagnosing combined faults in rotating machinery, incorporating data acquisition, preprocessing techniques, machine learning, and ensemble learning. Despite lacking multi-source data fusion, the CWRU dataset still allowed for the evaluation of the proposed methodology by considering multiple fault classes within the vibration data alone, resulting in a perplexing yet innovative approach.

The results showed promising performance across different algorithms. Figure 5 presented a bar plot showcasing the accuracy of each algorithm used in the study. The mean accuracy values, represented by blue dots, served as a visual reference for comparing the performance of different classifiers. Additionally, the error bars accompanying the mean accuracy values offered an indication of the standard deviation, capturing the variability around each mean. This information provided a comprehensive perspective on the accuracy measurements, helping to assess the robustness of the classifiers.

Among the base classifiers, the Logistic Regression achieves the highest accuracy of 94.2% followed closely by the KNN algorithm with 93.2% accuracy. Gaussian Naïve Bayes achieved an accuracy of 92.4%. However, the most impressive results were obtained from the Stacking Classifier, which achieved an accuracy of 97.2% and high precision, recall, and F1-score. The stacking approach, combining predictions from multiple base classifiers, proved highly effective in accurately diagnosing the 10 classes of faults based on the testing dataset. To gain deeper insights into the Stacking Classifier's performance, a confusion matrix is presented in Figure 4. The confusion matrix revealed a high number of correct predictions along the diagonal, indicating that the classifier accurately identified the 10 fault classes in the testing dataset. Furthermore, the convergence of the learning curves given in Figure 6 indicates that the model gradually improved its generalization capability, thereby reducing the performance gap between the training and test sets. This convergence is a positive indication that the model effectively learned from the training data and was able to generalize well to unseen test data. These findings highlight the effectiveness of the methodology and the potential of ensemble learning for accurately diagnosing multiple combined faults in rotating machinery, contributing to the maintenance and operational improvements in various industrial applications.

5 Conclusion

In conclusion, this study presented a comprehensive methodology for intelligent fault diagnosis of combined faults in rotating machinery using data fusion and machine learning techniques. Although the application of the methodology was carried out on the CWRU dataset, which did not include multi-source data fusion as it only utilized vibration signals, it successfully addressed the challenge of diagnosing combined faults by considering 10 fault classes in the bearing. Otherwise, by integrating multiple sensor data through the direct fusion model and leveraging machine learning algorithms and ensemble learning techniques, the proposed methodology can achieve a high level of accuracy and efficiency in diagnosing the multiple fault classes. The evaluation results on the vibration dataset demonstrated promising performance, with the ensemble learning model, particularly the Stacking Classifier, achieving an impressive accuracy of 97.2% and exhibiting high precision, recall, and F1-score.

While the dataset did not encompass the case of multi-source data fusion, the study effectively demonstrated the potential of the proposed methodology in diagnosing combined faults using vibration data alone. However, it is important to acknowledge that challenges still exist in accurately diagnosing combined faults, highlighting the need for further research to enhance accuracy and reliability. Overall, this study significantly contributes to the field of intelligent fault diagnosis by providing a comprehensive methodology and valuable insights for future research endeavors in this area.

6 Limitations And Future Scope

Although the presented methodology in this study displays promising outcomes for diagnosing combined faults in rotating machinery, there exist a few limitations and possibilities for improvement in the future.

Limited Dataset Availability, the availability of extensive and heterogeneous datasets is vital in the creation and assessment of fusion models. However, procuring accurately labeled datasets encompassing a wide range of combined fault scenarios can present significant challenges. As such, future research should focus on the collection and curation of comprehensive datasets that effectively capture the complexities and variations of combined faults in rotating machinery using a wide range of data sources.

Scalability and Adaptability, remain major challenges when applied to large-scale industrial systems that incorporate numerous sensors and complex fault scenarios. Ensuring the fusion models can handle high-dimensional data and accommodate evolving fault patterns is of utmost importance. In light of this, future research should explore techniques for developing scalable fusion model architectures and adaptive learning approaches to enhance their performance in real-world applications.

Data Uncertainty and Preprocessing, the accurate fusion and feature extraction of data collected from multiple sensors is hindered by the presence of noise and variability. In this study, particular data preprocessing techniques were implemented; however, it is imperative to explore alternative approaches to improve the robustness of fusion models. The establishment of standardized preprocessing methods for various sensors and fault analysis scenarios would be advantageous.

Incorporating Deep Learning Techniques, although machine learning techniques are utilized in this study, incorporating deep learning methods can yield valuable insights and elevate the accuracy of fault diagnosis. Complex patterns and representations in data can be captured effectively by deep learning algorithms, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs). future researchers need to explore the integration of deep learning techniques with the proposed data fusion approach to uncover hidden relationships and improve the precision of combined fault diagnosis in rotating machinery.

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