

INTELLIGENT ROLLING BEARING FAULT DIAGNOSIS UNDER SENSOR CHANNEL FAILURE USING IMAGE FUSION AND CNN-BILSTM DEEP LEARNING NETWORKS

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Abstract

Rolling bearings are essential components in large-scale and complex mechanical systems, where their operational reliability directly affects overall equipment safety. Under harsh working conditions, bearing fault diagnosis is often challenged by weak fault characteristics in one-dimensional vibration signals and performance degradation caused by sensor channel failures. To overcome these limitations, this study proposes an intelligent and adaptive rolling bearing fault diagnosis framework that integrates multi-channel image fusion with deep learning techniques. Initially, a threshold-driven channel assessment mechanism is introduced to identify and eliminate abnormal or failed sensing channels, followed by a bootstrap aggregation strategy to select representative and high-quality signal channels. Subsequently, vibration signals are transformed into two-dimensional feature representations using Gramian Angular Field encoding, and a multi-channel image fusion scheme is employed to enhance fault-related information. For efficient feature learning and classification, a convolutional neural network is adopted to extract discriminative spatial features and perform dimensionality reduction, while a bidirectional long short-term memory network is utilized to capture temporal dependencies and establish the relationship between extracted features and fault categories. The effectiveness and robustness of the proposed framework are evaluated through extensive simulation studies based on a benchmark rolling bearing vibration dataset with simulated sensor channel failure scenarios. Simulation results indicate that the proposed method achieves superior diagnostic accuracy and robustness compared with conventional CNN, LSTM, BiLSTM, and CNN-LSTM-based approaches. These findings demonstrate the potential of the proposed framework for reliable rolling bearing fault diagnosis in complex sensing environments with incomplete or unreliable measurement channels.

1. Introduction

With the rapid advancement of modern manufacturing systems, rotating machinery has become indispensable in industrial domains such as intelligent manufacturing, energy production, mining, aerospace, and transportation. As one of the most critical components in these systems, rolling bearings play a decisive role in maintaining operational stability and overall system efficiency. In practical applications, rolling bearings are often exposed to harsh operating conditions, which increases their susceptibility to degradation and failure, potentially leading to unplanned shutdowns and significant economic losses. Consequently, timely condition monitoring, fault detection, and maintenance of rolling bearings are essential for improving system reliability and minimizing accident risks [1-5]. Traditional maintenance strategies, however, typically require prolonged equipment downtime, resulting in production interruptions and elevated operational costs. In recent years, advances in sensing technologies, data acquisition systems, and computational intelligence have substantially enhanced the accuracy and efficiency of rolling bearing fault diagnosis, providing effective technical support for the continuous and reliable operation of industrial equipment under demanding conditions. As a result, research on intelligent fault diagnosis of rolling bearings has attracted growing attention due to its strong theoretical significance and practical value in equipment health management and cost-effective industrial operation.

Fault diagnosis represents a core research topic within industrial equipment health monitoring, aiming to accurately identify degradation and failure states during operation. Existing diagnostic approaches can generally be classified into two main categories: traditional signal processing-based techniques and data-driven machine learning-based methods. Signal processing approaches extract representative features from measured vibration signals to describe equipment conditions, typically utilizing time-domain, frequency-domain, or time-frequency-domain characteristics [6-11]. For rotating machinery applications, research efforts have predominantly

focused on frequency and time-frequency signal analysis techniques. Commonly employed methods include the fast Fourier transform (FFT), continuous wavelet transform (CWT), empirical mode decomposition (EMD), and variational mode decomposition (VMD) [12].

Among these techniques, EMD has been widely adopted for analysing nonlinear and non-stationary vibration signals in rolling bearing fault diagnosis since its introduction by Huang et al. [13]. Nevertheless, classical EMD often suffers from modal mixing, where frequency components from different intrinsic mode functions overlap, leading to inaccurate feature representation. To mitigate this limitation, Feng et al. introduced ensemble empirical mode decomposition (EEMD) by adding white noise to the original signal, thereby improving mode separation [14]. Despite this enhancement, residual modal mixing may still occur under certain operating conditions. To further address this issue, Dragomiretskiy et al. proposed variational mode decomposition (VMD), which formulates signal decomposition as a constrained variational problem [15]. However, the performance of VMD is highly dependent on the selection of key parameters, such as the number of modes and penalty factors. To overcome this dependency, He et al. developed an adaptive VMD approach that employs the artificial bee colony algorithm to optimise decomposition parameters based on a syncretic impact index [16]. Although this method improves fault feature extraction while suppressing noise and harmonic interference, it introduces additional computational complexity. Similarly, Shen et al. presented a bearing fault diagnosis framework integrating AGWO-PSO, VMD, time-energy feature construction, and AlexNet, where adaptive optimisation is used to enhance VMD performance under strong noise environments [17]. However, the combined optimisation strategy significantly increases computational burden, limiting its applicability for real-time online diagnosis. In addition, Zhou et al. proposed a hybrid approach combining complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and continuous wavelet

transform for rolling bearing vibration analysis [18]. While this method effectively highlights fault-related features, the iterative noise addition and repeated decomposition processes result in high computational costs, particularly for high-sampling-rate signals, thereby restricting its real-time monitoring potential.

In recent years, machine learning techniques, as an important branch of artificial intelligence, have been increasingly applied to fault diagnosis tasks to address complex pattern recognition and condition prediction problems. By learning discriminative features directly from historical data, data-driven diagnostic models enable effective detection and identification of equipment anomalies, thereby enhancing system reliability and maintenance decision-making efficiency. Commonly used machine learning algorithms in bearing fault diagnosis include random forests (RF), support vector machines (SVM), and artificial neural networks (ANN) [19]. For instance, Yang et al. proposed a roller bearing fault diagnosis approach that combines empirical mode decomposition energy entropy with ANN classification, where energy features extracted from different frequency bands serve as the input to the neural network, enabling accurate identification of bearing fault modes [20]. However, existing studies in this area often lack comprehensive comparative investigations that integrate EMD-based features with alternative signal decomposition techniques such as VMD or local mean decomposition, limiting their general applicability.

To further improve diagnostic performance, Wang et al. introduced a rolling bearing fault diagnosis framework that integrates recurrence quantification analysis (RQA) with a Bayesian-optimised support vector machine [21]. In this method, nonlinear dynamic features extracted via RQA are combined with Bayesian optimisation to automatically adjust SVM parameters, resulting in enhanced classification accuracy and robustness. Nevertheless, the stability of the extracted features under strong noise interference and their effectiveness in characterising different degradation stages were not thoroughly examined. In addition, Tang et al. developed a gearbox fault

diagnosis strategy based on a hybrid random forest classifier, in which compound faults are decomposed into single fault categories to reduce classification complexity and improve overall diagnostic performance [22]. Their study further emphasised that, although vibration-based analysis remains dominant in mechanical fault diagnosis, the integration of multi-source sensing data and collaborative multi-model frameworks is expected to become a key development direction for next-generation intelligent diagnostic systems.

Although traditional machine learning techniques have demonstrated promising performance in mechanical fault diagnosis, their limited generalisation capability when handling large-scale and complex datasets restricts their widespread deployment in real engineering applications. In contrast, deep learning methods leverage multilayer nonlinear architectures to automatically learn hierarchical feature representations directly from raw data, enabling end-to-end diagnostic modelling without manual feature engineering. This paradigm shift has significantly improved diagnostic accuracy, reduced response time, and lowered maintenance costs. For instance, Wu et al. introduced a one-dimensional convolutional neural network for automated feature extraction from rotor vibration signals to diagnose rub-impact faults [23]. While effective under controlled laboratory conditions, the robustness of this approach in complex industrial environments has yet to be fully validated. Yang et al. employed a CNN-based framework to extract preliminary fault features from rolling bearing vibration signals and combined gradient boosting decision trees with non-equivalent cost logistic regression to enhance diagnostic performance [24]. However, the computational burden associated with GBDT limits its suitability for real-time implementation. To further exploit temporal dependencies in vibration signals, Amin Khorram et al. proposed a convolutional long short-term memory recurrent neural network model that improves bearing fault diagnosis accuracy and efficiency without requiring extensive signal preprocessing [25]. Despite the advantages of such end-to-end architectures, their sensitivity to environmental

noise and reduced reliability under low signal-to-noise ratio conditions remain open challenges. Li et al. developed an anomaly detection framework termed CLKAN-RF, which integrates one-dimensional CNN, LSTM, and Kolmogorov-Arnold networks with an adaptive residual filtering mechanism to model spatiotemporal features of multivariate sensor data, achieving notable improvements in detection accuracy and robustness [26]. To address few-shot fault diagnosis with noisy labels, Wang et al. proposed the ETALF method, which combines a Transformer-based self-attention mechanism with an asymmetric loss function, attaining high diagnostic accuracies on the CWRU and KAIST datasets [27]. Song et al. presented an optimised CNN-BiLSTM framework for bearing fault diagnosis under limited training samples and multiple operating conditions [28]. However, the use of particle swarm optimisation for BiLSTM hyperparameter tuning introduces considerable computational overhead, reducing its practicality in resource-constrained environments.

Image-based deep learning approaches have also attracted significant attention in recent years. Nie et al. proposed an image-enhanced improved convolutional neural network (IEICNN) method that converts multi-channel vibration signals into RGB images and employs an improved SE-ResNet for feature extraction [29]. Although this approach achieves strong diagnostic performance, the deep image enhancement module results in increased processing time and reduced computational efficiency. To handle the complexity of gearbox operating environments, Chen et al. combined deep Q-networks with discrete random separation techniques for rolling bearing fault diagnosis, effectively isolating deterministic and random fault components [30]. Nevertheless, the exclusive reliance on DQN and the time-intensive training process limit the scalability of the approach, highlighting the need for algorithmic optimization and transfer learning strategies. Bai et al. introduced a hybrid diagnostic method integrating recursive point transformation, fractional Fourier transform, and CNN, successfully transferring RPT from gait recognition to bearing fault diagnosis [31]. However, this method focuses on

single-sensor data and does not exploit multi-source information, which constrains further improvements in diagnostic reliability. Overall, motivated by the strong performance of convolutional neural networks in image classification tasks, transforming one-dimensional time-series signals into image representations via specialized encoding schemes has emerged as an increasingly prominent research direction in intelligent fault diagnosis.

In recent years, the increasing complexity and variability of industrial operating environments have posed substantial challenges to intelligent fault diagnosis, particularly in cross-domain applications and real-time monitoring scenarios. Factors such as fluctuating operating conditions, sensor degradation, and channel failures often lead to a significant decline in diagnostic accuracy and generalization capability when conventional models lack adaptive mechanisms. To overcome these limitations, dynamic adaptation strategies have emerged as an important research direction for improving model robustness and adaptability. In the context of label-free cross-domain fault diagnosis for rotating machinery, Wang et al. proposed a dynamic collaborative adversarial domain adaptive network that employs a multi-objective generator adjustment mechanism, dual adversarial learning structures, and collaborative loss functions across multiple source domains, thereby enabling dynamic adaptation to varying data distributions and outperforming traditional static unsupervised domain adaptation approaches [32]. Dong et al. developed a global wavelet-integrated residual frequency attention network that combines wavelet-based residual structures with frequency-domain attention to enhance feature extraction resolution and robustness under complex conditions [33]. Similarly, Zeng et al. introduced an attention-guided hierarchical wavelet convolution network that reduces data redundancy through hierarchical wavelet decomposition and dynamically adjusts correlation weights across frequency bands using a time-frequency attention mechanism, allowing the model to focus on fault-sensitive frequency components [34-36]. Beyond single-sensor limitations, Wu et al. proposed an end-to-end deep

clustering framework for multi-sensor fault diagnosis, in which temporal and time-frequency features are extracted using a GRU autoencoder and a convolutional autoencoder, respectively, and adaptively fused through an attention-based modal integration strategy; unsupervised fault identification is then achieved using Kullback-Leibler divergence [37]. These studies collectively highlight the importance of adaptive learning, multi-source information fusion, and robustness enhancement in intelligent fault diagnosis, particularly under dynamic operating conditions and sensor reliability constraints.

Despite the substantial progress achieved by existing fault diagnosis approaches, several limitations still restrict their effectiveness in real-world engineering applications. First, conventional signal processing techniques exhibit limited capability when handling highly non-stationary and nonlinear vibration signals. Methods such as the fast Fourier transform, short-time Fourier transform, and continuous wavelet transform rely heavily on manually selected parameters, including window length and wavelet basis functions, which significantly influence diagnostic outcomes [38]. Moreover, these approaches often suffer from insufficient time-frequency resolution and weak energy representation, making them highly sensitive to noise and variations in operating conditions [39]. In addition, one-dimensional signal representations are often inadequate for fully capturing complex fault characteristics under dynamic operating environments, thereby constraining further improvements in diagnostic performance.

Second, in practical applications, diagnostic models based on single-channel image representations provide limited information and fail to reflect dynamic non-stationary behaviour. The lack of effective fusion strategies for multi-channel vibration data restricts the expressive power of signal representations, preventing the extraction of comprehensive global fault features and ultimately reducing classification accuracy and robustness [40-42]. Third, although traditional machine learning algorithms have been extensively applied in fault diagnosis, they still rely on manual

feature extraction. Identifying fault-sensitive features requires substantial expert knowledge, and inappropriate or excessive feature selection may introduce redundancy and lead to model overfitting. Finally, most existing studies primarily focus on offline fault diagnosis, while relatively limited attention has been given to online monitoring scenarios. In complex industrial environments, equipment operating conditions may change rapidly, especially in the presence of sensor degradation or channel failures. Under such circumstances, conventional diagnostic models often lack adaptive mechanisms to adjust monitoring strategies in real time, resulting in a notable degradation in diagnostic performance.

To overcome the limitations of existing approaches, this study proposes a dynamic and adaptive fault diagnosis framework for rolling bearings. Initially, a set of threshold criteria is employed to identify and remove faulty or low-quality sensor channels, followed by the selection of nine high-quality channels using a bagging-based ensemble strategy. The selected one-dimensional vibration signals are then transformed into two-dimensional images through Gramian Angular Difference Field (GADF) encoding, and subsequently spliced and fused to enhance feature representation. To ensure effective extraction of salient information from the fused images, a convolutional neural network combined with a bidirectional long short-term memory network (CNN-BiLSTM) is applied, enabling bidirectional feature learning that improves fault classification accuracy and robustness. The proposed method also supports online monitoring; in scenarios involving sensor degradation, it can dynamically adjust the fusion of remaining sensor channels to maintain real-time diagnostic capability. This adaptability demonstrates the method's robustness and practical applicability under complex operating conditions, including sensor failures, providing a reliable and flexible solution for industrial equipment health monitoring.

The remainder of the paper is structured as follows. Section 2 presents the theoretical foundation of the methodologies employed in the proposed fault diagnosis framework. Section 3

describes the experimental setup and details the step-by-step implementation of the diagnosis model. Section 4 analyses the results, highlighting factors influencing accuracy and robustness, and evaluating the framework's performance under sensor channel failures in online monitoring scenarios. Finally, Section 5 concludes the study and summarizes the key findings.

2. Fundamental Principles of the Applied Methodology

This section presents the essential theoretical concepts underlying the key methodologies utilized in this study, including the bagging algorithm, Gramian angular field encoding, convolutional neural networks (CNN), and bidirectional long short-term memory networks (BiLSTM). By integrating and enhancing these techniques, the section lays the groundwork for the design and implementation of the proposed

fault diagnosis framework, providing a solid theoretical basis for the methodological advancements presented in subsequent sections.

2.1. Ensemble Learning via Bootstrap Aggregation (Bagging)

The bagging algorithm, a classical ensemble learning technique, aims to improve model stability and predictive accuracy by combining multiple base learners trained in parallel [43]. The procedure is schematically depicted in Fig. 1. Initially, several bootstrap samples are generated by randomly selecting subsets from the original dataset with replacement. Each subset is used to independently train a decision tree or another base model. The outputs of all base learners are then aggregated, typically through majority voting for classification tasks, to produce the final prediction.

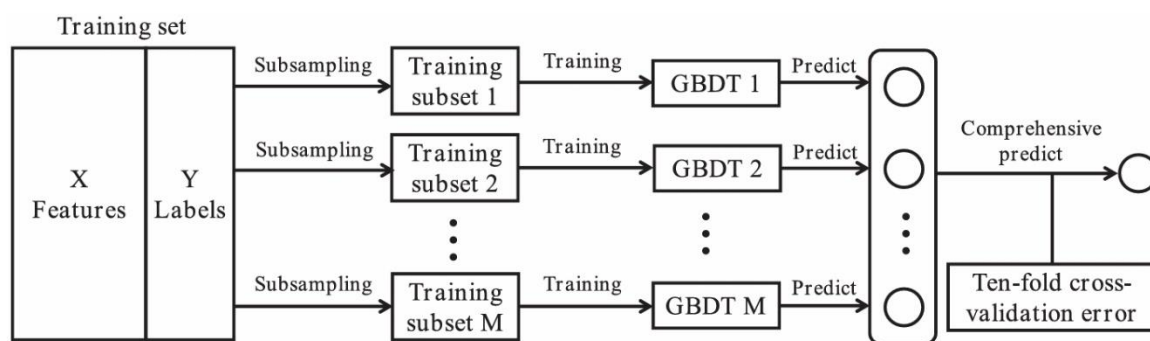


Fig. 1. Flowchart of bagging algorithm.

For performance evaluation, ten-fold cross-validation [44] is applied. In this approach, the original dataset is partitioned into ten equally sized folds, where nine folds are used for training and the remaining fold for testing. This process is repeated ten times, with each fold serving as the test set once. The cross-validation error is calculated as the proportion of incorrectly classified samples over the total number of samples across all iterations. By leveraging multiple models and diverse training subsets, the bagging algorithm enhances generalisation ability and reduces overfitting, making it well-suited for robust feature selection in multi-sensor fault diagnosis scenarios.

2.2. Time-Series to Image Encoding via Gramian Angular Field

The Gramian Angular Field (GAF) is a technique for converting one-dimensional time-series signals into two-dimensional images, effectively translating temporal dynamics into spatial representations. By encoding the temporal structure in this manner, GAF allows underlying patterns and variations within the data to be more readily captured and analysed. In recent years, GAF has been successfully applied to mechanical fault diagnosis tasks, demonstrating both robustness and high effectiveness in complex operational environments [45–49].

The method involves mapping the original time-series data from the Cartesian coordinate system

to a polar coordinate system, where each data point's magnitude is represented as a radius and its temporal position is encoded as an angular value. By constructing an angular field based on these angles, GAF captures the temporal correlations between different time points, reflecting the relationships and transitions across the signal sequence. This transformation enables image-based deep learning models, such as CNNs, to effectively extract spatial features that correspond to the temporal dependencies present in the original vibration signals.

2.3. Convolutional Neural Networks for Feature Extraction

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed to process visual data, achieving remarkable success in computer vision and image analysis tasks. Their effectiveness stems from a hierarchical feature learning mechanism, which automatically extracts representative patterns from raw input data through multiple layers. Two-dimensional CNNs (2D CNNs) are particularly common in image-based applications, including mechanical fault diagnosis [50-53].

A typical CNN consists of multiple layers that progressively process input data through forward propagation. Convolutional layers apply learnable filters to detect local features, such as edges or patterns, while pooling layers reduce the spatial dimensions of feature maps, lowering computational requirements and enhancing translation invariance [54-56]. After a series of convolutional and pooling operations, fully connected layers are often employed to integrate extracted features and map them to the output space corresponding to classification categories. The final output layer, often implemented as a softmax layer, generates a probability distribution over classes, where each value is non-negative and the sum equals one, enabling accurate classification of the input data.

The primary components of a standard CNN include:

- **Input layer:** Receives the raw data, typically images or other visual representations of signals.
- **Convolutional layer:** Extracts spatial and structural features from the input using convolution operations, capturing local patterns essential for downstream tasks.
- **Pooling layer:** Reduces the size of feature maps to decrease computational cost, prevent overfitting, and improve the model's robustness and translational invariance.
- **Softmax/output layer:** Produces a probability distribution across all output classes, enabling classification by identifying the most likely category for the input.

By automatically learning hierarchical representations, CNNs eliminate the need for manual feature engineering, making them highly suitable for fault diagnosis tasks where complex patterns in vibration or image-transformed signals must be captured efficiently.

2.4. Bidirectional Long Short-Term Memory Networks for Sequential Feature Learning

Traditional Recurrent Neural Networks (RNNs), which extend feedforward networks to handle sequential data, often face difficulties such as gradient vanishing and gradient explosion when processing long sequences. These issues arise because gradient information must be propagated through multiple time steps during backpropagation, leading to either rapid decay or uncontrolled growth of gradients over long sequences. LSTM incorporates three gating mechanisms, forget, input, and output gates, which enable the network to selectively retain, update, or output information, allowing it to efficiently model long-term dependencies in sequential data. The architecture of a standard LSTM unit is illustrated in Fig. 2.

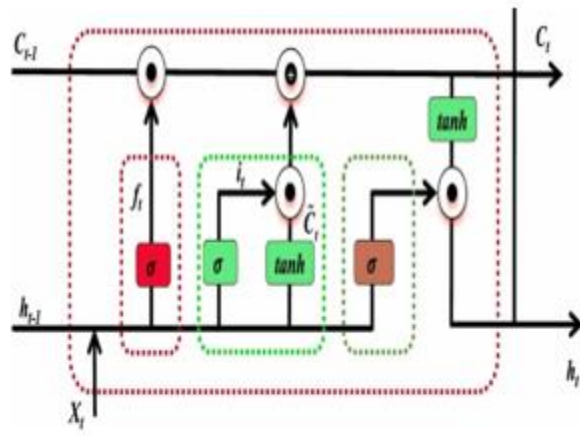


Figure 2

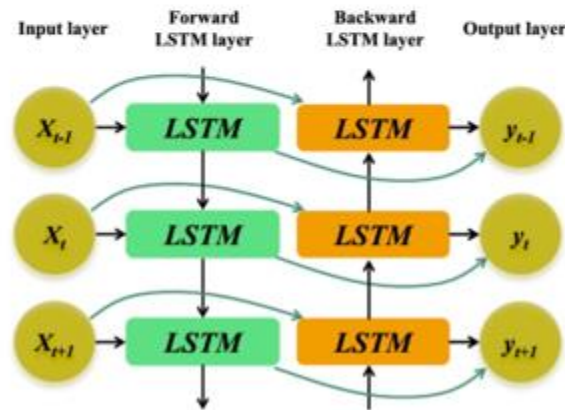


Figure 3

Unlike conventional LSTM, which processes sequences in a single (forward) direction, Bidirectional LSTM (BiLSTM) leverages both forward and backward passes to capture contextual information from past and future states simultaneously, enhancing feature representation and improving prediction accuracy [57]. In a BiLSTM, the forward LSTM layer processes the sequence from the first to the last time step, storing intermediate outputs, while a backward LSTM layer processes the sequence in reverse. The outputs from both directions are then concatenated to form the final representation. As shown in Fig. 3, a BiLSTM layer effectively consists of two parallel LSTM layers; one moving forward and the other backward whose outputs are combined, enabling the network to extract richer temporal features and better capture the

sequential dependencies inherent in vibration signals for fault diagnosis tasks.

3. Dynamic Fault Diagnosis Framework Using Multi-Channel Image Fusion and Deep Learning

To overcome the limitations of incomplete feature representation in single-channel temporal signals and two-dimensional images, as well as to address sensor channel failures, this study proposes a dynamic adaptive fault diagnosis framework that integrates multi-channel image fusion with deep learning. The workflow of the proposed method is divided into three main components:

Part A: Experimental Setup and Signal Acquisition – This step establishes a rolling bearing experimental platform to generate reliable vibration data under various fault conditions,

providing a solid foundation for model training and evaluation.

Part B: Fault Diagnosis Using Multi-Channel Image Fusion and Deep Learning – This component consists of three sub-steps:

- **B1 Adaptive Channel Selection:** Assess the health of each sensor channel, rank their quality, and exclude low-quality or faulty channels, ensuring that only high-quality signals are used for subsequent analysis.
- **B2 Signal Conversion and Image Fusion:** Transform the selected time-series signals into images and fuse multi-channel representations, providing a more comprehensive depiction of equipment operating status.
- **B3 CNN-BiLSTM Network Model:** Extract spatial features from fused images using a CNN, while capturing temporal relationships through the BiLSTM network. This combination enables accurate analysis of dynamic signals and effective fault classification.

Part C: Offline and Online Validation – The proposed method is evaluated from both offline and online perspectives to verify its effectiveness under different conditions, including real-time scenarios with sensor channel failures. The results of this validation are presented in Section 4.

3.1. Adaptive Sensor Channel Evaluation

In rolling bearing condition monitoring and fault diagnosis, sensor failures, environmental noise, and outlier measurements can lead to false alarms or missed detections. To ensure that the 12-channel vibration data collected from sensors is reliable and free from abnormal interference, it is necessary to perform a health verification step during data preprocessing.

This section introduces a threshold-based channel evaluation method that adaptively assesses the integrity of each sensor channel. Both time-domain and frequency-domain features are extracted and compared against statistically derived thresholds. Time-domain features, including standard deviation, peak factor, and steepness, are used to evaluate signal variability and detect anomalies. Frequency-domain features, such as main frequency energy, high-frequency

energy ratio, and energy entropy, are calculated to assess the quality of each signal.

Based on these features, a quantitative health score is assigned to each channel. For each feature, a score of 1 is given if the value falls within the acceptable threshold range, and 0 if it exceeds the threshold. The overall health score of a channel is obtained by averaging all feature scores, resulting in a value between 0 and 1. Channels with a health score greater than 0.9 are considered healthy. A channel is classified as healthy if it simultaneously satisfies all the following criteria: standard deviation greater than or equal to its threshold, peak factor less than or equal to its threshold, steepness less than or equal to its threshold, main frequency energy greater than or equal to its threshold, and high-frequency energy ratio less than or equal to its corresponding threshold.

This adaptive evaluation ensures that only high-quality signals are used for subsequent image transformation and fault diagnosis, enhancing the robustness and reliability of the proposed method. According to the threshold-based channel evaluation criterion proposed in this study, the data from 12 sensor channels under three different load conditions were validated. The results indicate that all channels met the healthy criteria, and no abnormal channels were detected. To further assess the robustness of this evaluation method, common types of sensor failures were simulated. Four channels (Channels 3, 6, 8, and 12) were selected, each subjected to a specific failure scenario [58-60].

- **Signal loss (all-zero signal):** In Channel 3, the signal was set to zero between 20 s and 30 s, simulating a disconnected signal or sensor failure.
- **Periodic pulsed disturbance:** Channel 6 had a superimposed periodic pulse from 20 s to 30 s, simulating interference caused by mechanical vibrations or repeated impacts.
- **High-amplitude random noise interference:** Channel 8 introduced high-amplitude random noise from 20 s to 30 s, representing abnormal fluctuations due to electromagnetic interference or environmental disturbances.
- **Out-of-range signals:** Channel 12 generated a constant, high-amplitude signal

between 20 s and 30 s, mimicking a hardware fault where the sensor output exceeds its physical limits. The evaluation successfully identified all four channels as abnormal, demonstrating that the proposed threshold-based criterion is robust and capable of detecting various types of sensor failures, including signal loss, periodic disturbances, high-amplitude noise, and out-of-range signals. These validation results confirm the effectiveness of the method in monitoring rolling bearing conditions and ensuring high-quality data for subsequent fault diagnosis algorithms.

After excluding damaged sensors, the remaining channels are further evaluated using the bagging algorithm from ensemble learning to enhance the accuracy and stability of the fault diagnosis model. To illustrate this process, a demonstration case without any sensor failure is considered. Ten-fold cross-validation is applied to the data from all 12 channels, and the resulting error values are shown in Fig. 4. When ranked from lowest to highest error, the channels are ordered as follows: 3, 12, 10, 6, 8, 7, 9, 4, 11, 5, 2, and 1, indicating their quality

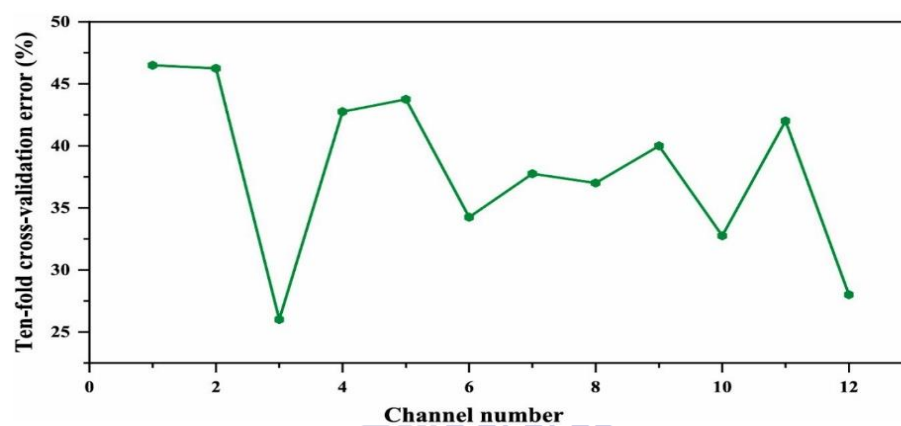


Figure 4

from high to low. To improve model performance, the nine channels with the lowest error are selected for subsequent signal processing and image fusion. This selection ensures that high-quality channels contribute to the analysis, enhancing the stability, generalization, and reliability of the resulting fused images used for fault diagnosis.

3.2. Signal Conversion and Multi-Channel Image Fusion

After completing adaptive channel selection and identifying nine high-quality channels, the one-dimensional vibration signals from these channels are transformed into two-dimensional images and subsequently fused. The process involves the following steps:

Step 1: One-Dimensional Signal Acquisition

Based on the channel quality evaluation, the nine selected channels are prioritised in the following order: Channel 3, 12, 10, 6, 8, 7, 9, 4, and 11. Using the highest-quality Channel 3 as an example, its raw vibration signal can be represented as a discrete sequence $X_{CH3} = \{x_1, x_2, \dots, x_t, \dots, x_L\}$, where x_t denotes the acceleration value at time t and the signal length L is 1024.

Step 2: GADF Image Transformation

Each one-dimensional signal is converted into a Gramian Angular Difference Field (GADF) matrix using the method described in Formula (5). For Channel 3, the resulting matrix $GADF_{CH3}$ has dimensions of 1024×1024 , preserving the temporal structure of the original vibration signal. The same process is applied to the remaining channels.

Step 3: Multi-Channel Image Fusion and Size Standardisation

The individual GADF matrices from the selected channels are fused to form a comprehensive multi-channel representation. To optimise storage and facilitate model input, the fused matrix

$GADF_{fused}$ is resized to a standard 128×128 pixel image, denoted as $GADF_{imagefusion}$. This step also addresses potential size mismatches caused by sensor anomalies or future system expension

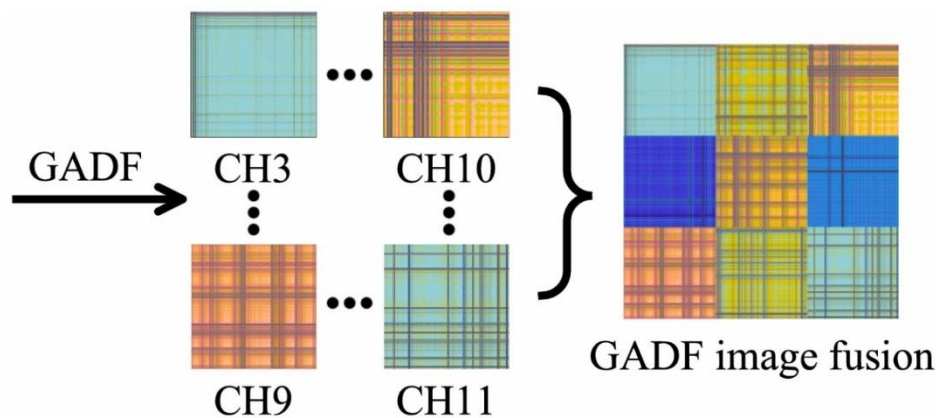


Figure 5

The resulting standardized fused image, shown in Fig. 5, serves as the input for the subsequent CNN-BiLSTM network. This multi-channel fusion strategy provides a robust representation of the

equipment's operating status, forming a solid foundation for feature extraction and accurate fault classification.

3.4. CNN-BiLSTM Network Model

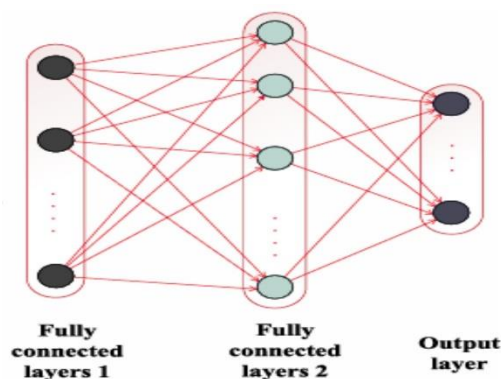


Figure 6

The proposed CNN-BiLSTM model, shown in Fig. 6, consists of 13 layers: one input layer, four convolutional layers, four pooling layers, one BiLSTM layer, two fully connected layers, and one output layer.

The model processes the fused GADF image $GADF_{imagefusion}$ as input. While the original image is grayscale, it is converted into an RGB format to enhance feature extraction. By mapping information across the three RGB channels, the network can capture richer spatial features and

finer details. The input to the first convolutional layer is therefore a three-channel RGB image $GADF_{imagefusion_RGB} \in \mathbb{R}^{H \times W \times C}$, where $H = 128$ and $W = 128$ denote the height and width of the image in pixels, and $C = 3$ represents the number of RGB channels.

Let X^{l-1} represent the input feature map to the l^{th} convolutional layer. The convolutional layers extract spatial features from the fused image using learnable filters, while the pooling layers reduce the spatial dimensions of the feature maps, lowering computational cost and enhancing translational invariance. Following the convolutional and pooling stages, the BiLSTM layer captures temporal dependencies in the sequential features derived from the image, allowing the model to learn dynamic patterns and correlations across different regions of the fused image.

Finally, two fully connected layers integrate the extracted features, and the output layer generates the classification results corresponding to different fault types. This combined CNN-BiLSTM architecture effectively leverages both spatial and temporal information in the fused vibration images, improving fault diagnosis accuracy and robustness under varying operating conditions.

4. Results and Discussions

This study proposes a dynamic adaptive fault diagnosis method based on multi-channel image fusion and deep learning. The approach can autonomously detect and exclude failed sensor channels in the presence of sensor damage or abnormal signals, ensuring that accurate fault diagnosis is maintained using the remaining functional sensors.

To evaluate the effectiveness of the proposed method, this section presents a detailed discussion of the experimental and simulation results. The analysis examines the key factors influencing the fault diagnosis performance of rolling bearings from multiple perspectives, including operational load conditions and varying noise levels. Special attention is given to the robustness and stability of the method under different scenarios, as well as comparisons with existing fault diagnosis

approaches to highlight its performance advantages.

To account for the impact of random initialization in the training process, all experiments were repeated independently five times. The performance of the fault diagnosis model is quantitatively assessed using the following metrics: Fault Diagnosis Accuracy (FDA), Average Fault Diagnosis Accuracy (AFDA), Standard Deviation of Accuracy (SDoA), Average Sensitivity (ASe), Average Specificity (ASp), Average Precision (AP), Average F1 score (AF1), and Average Running Time (ART). These metrics provide a comprehensive evaluation of the method's accuracy, reliability, and computational efficiency.

4.1. Impact of Pixel Resolution on Fault Diagnosis

An important consideration in this study is how the pixel size of GADF-transformed images affects the accuracy and efficiency of fault classification using the CNN-BiLSTM network. The image resolution directly influences the amount of information captured, as well as the computational demands and depth requirements of the model. Images with very small pixels may fail to capture sufficient detail, leading to incomplete feature representation and reduced diagnosis accuracy. Conversely, excessively large pixels increase computational load and prolong training and testing times.

As observed, higher-resolution images contain more detailed features, which increases both training and testing time due to greater computational requirements. Images sized 32×32 pixels allow for faster training and testing but result in lower accuracy. A resolution of 64×64 pixels provides a better balance between accuracy and computational cost. Images of 128×128 pixels achieve the highest accuracy while maintaining manageable processing time. In contrast, 256×256 pixel images substantially increase computational costs without yielding proportional gains in accuracy, making them less suitable for real-time or resource-constrained applications.

Based on these observations, a resolution of 128×128 pixels was selected in this study. This choice

effectively preserves the essential signal information while keeping computational complexity and training time within practical limits. With this configuration, the CNN-BiLSTM model can efficiently process fused images and perform accurate fault classification.

4.2. Impact of Multi-Channel Image Fusion on Fault Diagnosis

Signal conversion and image fusion play a crucial role in the proposed dynamic adaptive fault diagnosis framework, enabling effective processing and analysis of multi-channel sensor data to improve fault detection accuracy. While the influence of pixel resolution on GADF-fused images has been discussed previously, it is equally important to examine the effect of the number of channels and the image fusion arrangement on diagnosis performance. Different configurations, such as sensor anomalies or system expansion, can lead to varying input image sizes. To ensure the generality of the fault diagnosis model, it is essential to maintain consistent input image dimensions.

Based on the ten-fold cross-validation, high-quality channels were selected, converted into GADF images, and fused into composite images. Direct horizontal or vertical splicing of GADF images may result in inconsistent dimensions, so square arrangements (e.g., 1×1 , 2×2 , 3×3) are preferred. These fused images can then be resized to meet application requirements. In practical engineering, the number of selected channels may not always form a perfect square. In such cases, blank images can be used as placeholders to create complete fused images.

Using this approach, GADF transformation was applied to the 12-channel dataset. Selected channels were fused into square images and resized to 128×128 pixels before being fed into the CNN-BiLSTM model. Specifically, the 3×3

fusion of nine channels achieved the highest average accuracy of 99.48 %, demonstrating the effectiveness of incorporating multiple sensors.

Increasing the number of fused channels improves diagnosis stability and robustness, as evidenced by the more concentrated distribution of accuracies when four to nine channels are fused. However, fusing more channels also increases image fusion time, computational cost, and model training time. Moreover, introducing blank images as placeholders may slightly reduce precision, as seen in minor deviations in accuracy for 4-channel versus 5-channel fusion or 9-channel versus 10-channel fusion.

Overall, these results show that an appropriately designed multi-channel image fusion strategy can effectively capture key fault features from complex signals, significantly enhancing the accuracy, robustness, and practical applicability of the fault diagnosis model.

4.3. Evaluation of Different Image Fusion Strategies

Image fusion is a critical element of the proposed fault diagnosis method, as the fusion strategy directly impacts model performance. This section evaluates and compares the effectiveness of various image fusion strategies to determine the optimal approach for rolling bearing fault diagnosis.

4.3.1. Comparative Analysis of GADF and GASF Fusion

The Gramian angular field can be represented as either the Gramian Angular Difference Field (GADF) or the Gramian Angular Summation Field (GASF). To assess their performance, GADF and GASF images were independently fused and input into the CNN-BiLSTM network for comparison. The corresponding loss curves are shown in Fig. 7 and 8.

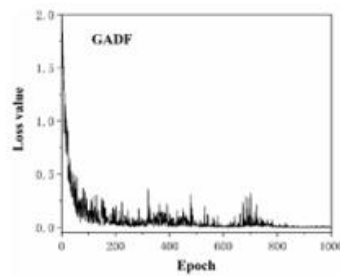


Figure 7

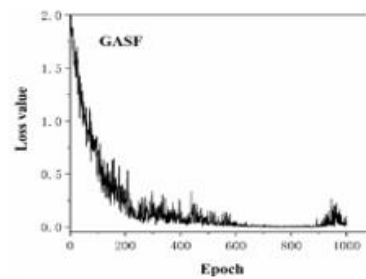


Figure 8

As seen in Fig. 7, the GASF-fused images show convergence to a near-zero loss around 600 iterations. However, the loss fluctuates again after 900 iterations, indicating instability in the GASF fusion process. In contrast, Fig. 8 shows that the GADF-fused images achieve convergence after 800 iterations, with significantly smoother loss reduction and minimal fluctuation. This demonstrates that GADF fusion provides higher stability and more reliable optimization for the CNN-BiLSTM network, making it more suitable for scenarios that require consistent and robust fault diagnosis. Based on these results, GADF-fused images were selected for subsequent experiments.

4.3.2. Exploration of Hybrid Image Fusion

While GADF fusion outperforms GASF fusion, the potential for combining both fusion types to enhance fault diagnosis remains worth exploring. In this study, six hybrid image fusion strategies were designed, and the resulting fused images were input into the CNN-BiLSTM model. The performance of these hybrid strategies was compared against the single-type fusion methods (GADF and GASF).

Fusion Strategy I: Weighted Complementary Fusion

The weights of the GADF and GASF images were determined using the bagging algorithm. The images were then linearly combined based on these weights. The fused images from nine selected channels were integrated to form a complete input for the CNN-BiLSTM network.

Fusion Strategy II: Weight-Based Selection

For each channel, the image type (GADF or GASF) with the higher weight was chosen for fusion. This approach enhances the robustness of image selection and improves the overall quality of the fused image.

Fusion Strategy III: Information Entropy

Information entropy measures the uncertainty or information content in data. Images with higher entropy contain more unique and complex information, which is often indicative of richer fault-related features [44]. By prioritizing channels with higher information entropy, the fused images capture critical fault details more effectively, improving diagnosis accuracy.

Fusion Strategy IV: Energy Entropy

Energy entropy measures the complexity and distribution of signal energy across different frequency or spatial domains, reflecting the concentration or dispersion of energy in the signal. In GADF and GASF images, channels with higher energy entropy often contain richer information related to specific failure modes. By prioritizing these channels, the differences in energy characteristics are emphasized in the fused image, providing valuable features for classification models and enhancing fault diagnosis accuracy.

Fusion Strategy V: Sample Entropy

Sample entropy quantifies the complexity and unpredictability of signals, with higher values indicating greater randomness and dynamic variation [46]. This measure helps identify

channels containing more intricate signal patterns. Selecting images from channels with higher sample entropy ensures that subtle fault features are preserved in the fused image, improving the detection of complex or overlapping fault modes.

Fusion Strategy VI: Mixed Entropy

The mixed entropy strategy combines information entropy, energy entropy, and sample entropy to select the most representative image for each channel. By evaluating multiple aspects of signal complexity and feature richness, this approach ensures that the final fused image captures critical fault information from all relevant perspectives. This comprehensive selection enhances the overall quality of image fusion and supports more accurate and robust fault diagnosis.

4.3.2.7. Summary of Image Fusion Results

The performance of eight image fusion strategies, including GADF, GASF, and six hybrid methods. The results indicate that using either GADF or GASF images alone outperforms all hybrid fusion strategies. Specifically, GADF image fusion achieves an average fault diagnosis accuracy of 99.48 %, exceeding the 97.04 % accuracy of GASF fusion, while also exhibiting smaller fluctuations. Among the six hybrid fusion strategies, only the weighted-determined fusion shows competitive performance, achieving 96.76 % accuracy with a narrow error range. In contrast, the weighted complementary fusion underperforms, reaching just 59.94 %, likely due to feature dilution when

combining GADF and GASF images, which weakens the fault-specific information. The entropy-based strategies—information entropy, energy entropy, sample entropy, and mixed entropy—yield average accuracies of 93.12 %, 94.29 %, 95.95 %, and 95.76 %, respectively. Although these methods can select representative images, their diagnostic performance does not surpass the weighted-determined fusion strategy. Overall, while hybrid fusion theoretically enhances feature expressiveness, GADF images consistently provide higher accuracy and stability. Their ability to effectively capture fault characteristics, coupled with lower computational complexity, makes them a superior choice for practical bearing fault diagnosis. These findings confirm that GADF image fusion offers a reliable and efficient solution for industrial fault diagnosis tasks.

4.4. Fault Diagnosis Accuracy under Different Load Conditions

In industrial environments, variations in load conditions can significantly affect the accuracy of fault diagnosis. In this study, the experimental platform allows precise load control through adjustment of the eddy current brake input current, enabling diverse training and testing datasets. Three load scenarios were evaluated: no load (0.0 A), light load (0.3 A), and moderate load (0.5 A). Confusion matrices for these scenarios are presented in Fig. 9, with the horizontal and vertical axes representing the seven states of rolling bearings.

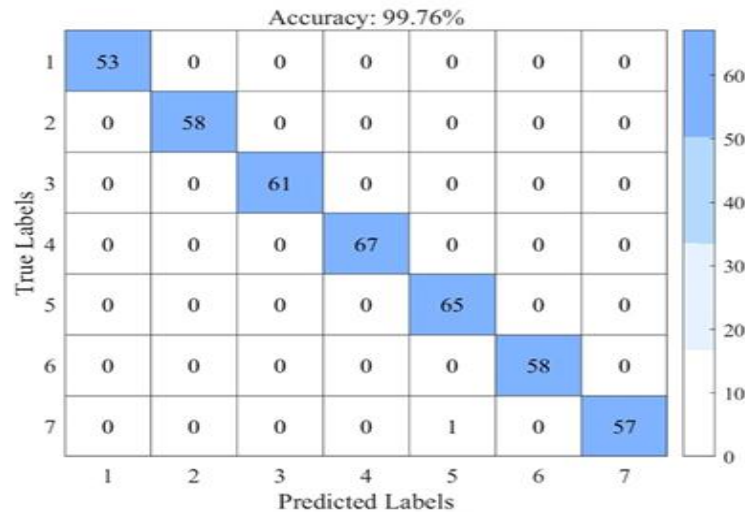


Figure 7

Under no-load conditions, the CNN-BiLSTM model achieves a single-run accuracy of 99.76 %. At a 0.3 A load, the model maintains high performance with 99.05 % accuracy. Remarkably, under a 0.5 A load, the model attains perfect classification with 100 % accuracy. These results demonstrate that the proposed fault diagnosis approach reliably identifies all seven bearing states across varying loads, confirming its robustness, adaptability, and applicability in multi-load industrial scenarios.

In summary, combining GADF image fusion with the CNN-BiLSTM model provides a highly accurate and stable method for rolling bearing fault diagnosis, ensuring reliable performance under diverse operational conditions.

4.5. Comparative Analysis of Fault Diagnosis Methods

While image fusion enhances the richness of fault information, it is essential to evaluate whether the proposed CNN BiLSTM network outperforms conventional models such as CNN, LSTM, BiLSTM, and hybrid models like CNN LSTM. To address this, GADF fused images are used as input to systematically compare the fault recognition capabilities of these models. Seven key metrics, AFDA, SDoA, ASe, ASp, AP, AF1, and ART, are employed to provide a comprehensive evaluation

of performance across accuracy, robustness, and efficiency.

The experimental results reveal that the CNN BiLSTM model consistently outperforms all other models. Specifically, CNN BiLSTM achieves the highest AFDA of 99.48 percent, surpassing CNN LSTM (98.47 percent), CNN (97.66 percent), BiLSTM (77.24 percent), and LSTM (74.10 percent). The model also demonstrates the lowest standard deviation of accuracy, reflecting superior stability. Other performance metrics including ASe, ASp, AP, and AF1 approach 100 percent, indicating outstanding fault recognition capability.

Regarding efficiency, the CNN BiLSTM model processes a single test case in 0.0059 seconds, slightly longer than CNN (0.0054 seconds) and CNN LSTM (0.00568 seconds) but significantly faster than LSTM (0.00987 seconds) and BiLSTM (0.01405 seconds). This confirms its suitability for real time fault diagnosis. Analysis of individual models shows that LSTM and BiLSTM underperform due to limited image feature extraction, while CNN excels in spatial feature processing but cannot fully capture temporal dynamics. CNN LSTM improves performance by combining spatial and temporal processing, yet it remains slightly inferior to CNN BiLSTM. Overall, the CNN BiLSTM model effectively integrates CNN's spatial feature extraction with

BiLSTM's bidirectional temporal modeling, achieving superior accuracy, robustness, and efficiency.

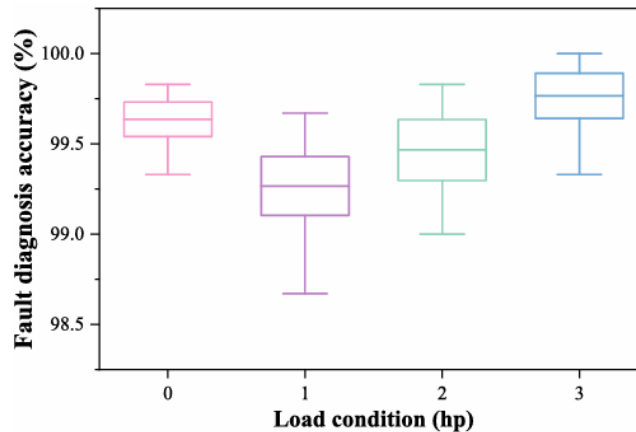


Figure 10

To further validate the proposed method, experiments were conducted on two benchmark datasets: the Case Western Reserve University bearing dataset [47] and the Southeast University rotor experiment dataset [48]. On the CWRU dataset, the method achieves near perfect fault classification across four load conditions, 0 hp, 1 hp, 2 hp, and 3 hp, as shown in Fig. 10. For the SEU dataset, fault classification accuracy reaches 100 percent under both 20 Hz 0 V and 30 Hz 2 V operating conditions, Fig. 10, demonstrating strong generalization ability and reliability across different operating scenarios.

A comparison with existing literature further highlights the method's superiority. On the CWRU dataset, the proposed approach outperforms AMCEMD 1DCNN1DCNN [49] (99.5 percent), AT ICNN [50] (98.12 percent), POA VMD GADF Swin Transformer [51] (98.72 percent), and LSTM TCN [52] (99.56 percent). On the SEU dataset, it exceeds TFP MCL [53] (99.8 percent), ATFMD SGET [54] (99.37 percent), and RC STGNN [55] (99.44 percent). These results confirm the effectiveness and practical advantages of the CNN BiLSTM model with GADF image fusion for rolling bearing fault diagnosis.

5. Conclusions

To address the limitations of traditional fault diagnosis methods in complex and dynamic industrial environments, particularly in unexpected situations such as sensor damage that can reduce diagnosis accuracy, and considering that conventional methods usually lack online monitoring capabilities, this paper proposes a dynamic adaptive fault diagnosis method based on multi-channel image fusion and deep learning. Through experimental comparisons and analyses, the following conclusions are drawn:

- The threshold-based channel evaluation criterion can adaptively exclude abnormal channels, while the bagging algorithm assesses the signal quality of the remaining normal channels. This channel evaluation strategy provides high-quality signals for subsequent analysis and prevents interference from unreliable data. The GADF image fusion strategy offers more comprehensive and richer fault features compared to the GASF image fusion strategy and six hybrid fusion strategies, effectively enhancing the representation of equipment status.
- Comparison with four different deep learning models demonstrates that the CNN BiLSTM model can extract fault features more comprehensively and significantly improve diagnostic performance.

- The proposed method performs effectively under noise interference and varying operating conditions. Experiments validate its strong noise resistance in medium to low signal-to-noise ratio environments and show excellent performance across different load and working conditions.
- The method is capable of real-time analysis of equipment status, providing rapid diagnostic results and early warnings when faults occur. This significantly improves the safety and operational efficiency of industrial equipment. Overall, this study fully validates the effectiveness of the proposed method for bearing fault diagnosis. It is capable of offline fault diagnosis while also supporting online fault detection under channel failure. However, there remain opportunities for further research. Future work will focus on enhancing the fusion of multiple data types such as current, temperature, and sound, improving the real-time predictive performance of monitoring systems, and expanding the application of this method to offer a more cost-effective solution for bearing fault diagnosis in complex industrial environments.

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