DOI: 10.21062/mft.2025.048 http://www.journalmt.com

Fault Diagnosis of Electric Motor Rotor Systems Based on Feature Extraction and CNN-BiGRU-Attention

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To enhance the accuracy of fault diagnosis (FD) in motor rotor systems, this study introduces a novel method that leverages feature extraction (FE) combined with a CNN-BiGRU-Attention deep learning model. Initially, the time-domain features of the vibration signals are extracted using Variational Mode Decomposition (VMD), which also effectively denoises the data. Subsequently, the frequency-domain features of the vibration signals are extracted via Fast Fourier Transform (FFT). The aggregated features are then fed into the CNN-BiGRU-Attention model to perform fault classification. In this model, the Convolutional Neural Network (CNN) module extracts local spatial features, the Bidirectional Gated Recurrent Unit (BiGRU) module models the temporal dependencies, and the Attention mechanism enhances the focus on critical fault information, thereby improving the model's classification performance. Experimental results demonstrate that the proposed FD method achieves an accuracy of 99.58%. Compared to other commonly used models, the performance metrics of our model show significant advantages and superior performance.

Keywords: Electric motor rotor system; Fault diagnosis; Variational mode decomposition; Fast fourier transform; CNN-BiGRU-Attention model

1 Introduction

The rotor system of an electric motor constitutes a critical component in large-scale mechanical equipment, directly influencing the performance and safety of the apparatus. Accurate diagnosis of faults within the rotor system is paramount for preventing equipment downtime, extending operational longevity, and reducing maintenance costs [1].

FD based on vibration signals currently stands as a prevalent method for mechanical fault detection. Mechanical vibration signals exhibit characteristics of imbalance and non-linearity. Extracting effective features from these signals is a prerequisite for FD [2]. Research documented in Reference [3] employs Variational Mode Decomposition (VMD) for the adaptive decomposition of complex signals and enhances FE through the integration of Variable Step-Size Filtering Waveform VMD (VFW-VMD), thereby improving the signal processing's noise resistance and robustness. Reference [4] utilizes Fast Fourier Transform (FFT) for frequency domain analysis, combined with Sparse Discrete Fourier Transform (SparseDFT) to enhance computational efficiency, which is widely used in signal processing and frequency analysis. Furthermore, Reference [5] applies the VMD method to decompose vibration signals of rolling bearings to obtain multiple modal components. Subsequent spectral analysis of these modal components through FFT allows for the extraction of principal fault characteristics, thereby enhancing the accuracy of the diagnosis.

In recent years, deep learning has been extensively applied in the FD of mechanical equipment. Among the various deep learning algorithms, Convolutional Neural Networks (CNN) [6] and Recurrent Neural Networks (RNN) [7] have demonstrated exceptional performance. However, the use of a single CNN or RNN presents certain limitations in handling the temporal and spatial features of complex signals. Consequently, models that combine features of CNNs and RNNs have been proposed. Reference [8] introduces a deep model based on CNN and Long Short-Term Memory (LSTM) networks for the spatial extraction and temporal modeling of fault characteristics, significantly enhancing diagnostic precision. Reference [9] describes a model that integrates Multi-Scale CNNs with Bidirectional Gated Recurrent Units (BiGRU) for extracting spatial and temporal features in high-noise environments, thereby improving FD accuracy. Reference [10] proposes a hybrid model combining Multi-Layer Perceptrons (MLP) with LSTM, achieving dual functionality in bearing FD and remaining life prediction.

This study introduces an FD method for rotor systems based on FE and a CNN-BiGRU-Attention model. We utilize VMD and FFT to extract time-frequency domain features from vibration signals, which serve as inputs for the constructed CNN-BiGRU-Attention model to diagnose rotor system faults. The CNN extracts local features, the BiGRU captures temporal dependencies, and the Attention mechanism enhances key features, all aimed at improving diagnostic accuracy.

2 Methodology for FD in Rotor Systems

In order to effectively extract fault characteristic information from nonlinear, non-stationary vibration signals and enhance the precision of FD in rotor systems, this study introduces an FD methodology based on FE and a CNN-BiGRU-Attention model. The principle of this method is illustrated in Figure 1.

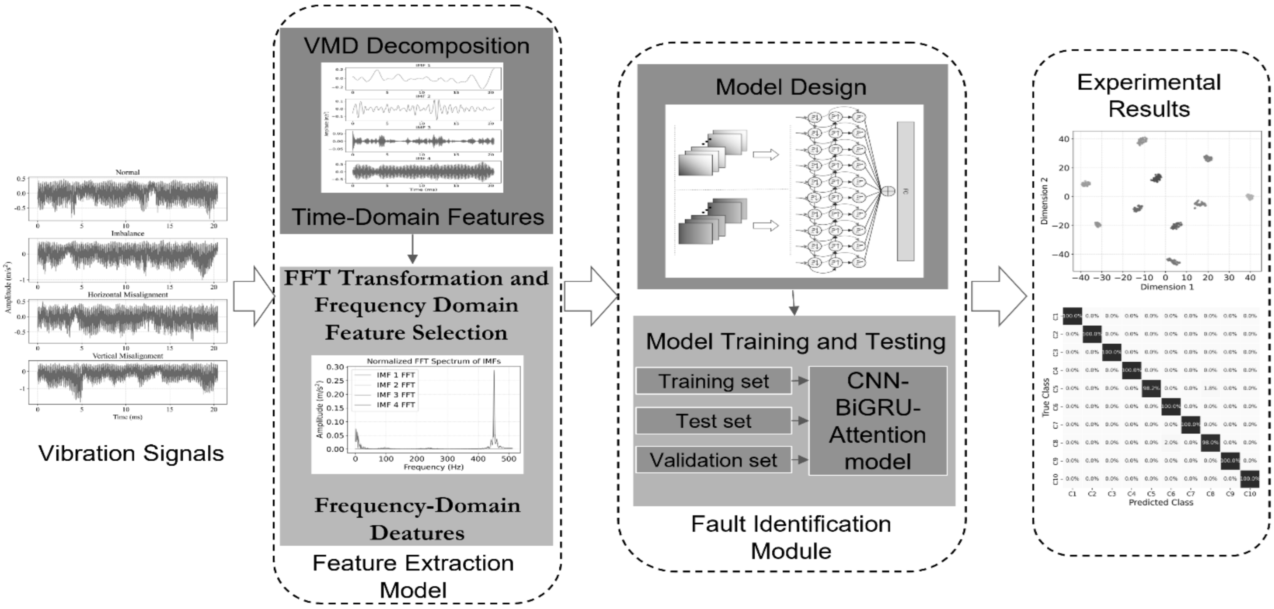

Fig. 1 *FD model based on FE and CNN-BiGRU-Attention*

The diagnostic model for rotor systems based on the FE and CNN-BiGRU-Attention model comprises an FE module and a fault identification module.

- 1) FE Module: Initially, the raw signal is decomposed into time domain components using VMD, from which time domain features are extracted. Subsequently, these components undergo an FFT to derive frequency domain features. The correlation coefficients of these frequency domain features are calculated, and the optimal frequency domain components are combined with the time domain features post-VMD decomposition.
- 2) Fault Identification Module: The combined time-frequency domain features are proportionally divided into datasets. These datasets are then utilized as inputs for the CNN-BiGRU-Attention model to classify faults.

2.1 FE Module

2.1.1 VMD Decomposition

VMD is a classical algorithm for time-frequency signal analysis. Compared to the traditional Empirical Mode Decomposition (EMD), VMD is grounded in a more robust mathematical framework and exhibits superior decomposition capabilities. VMD transforms the signal decomposition process into a non-recursive mathematical optimization problem by constructing a variational problem. Solutions are iteratively sought to optimally decompose the signal into its modal components, termed IMFs. This method effectively suppresses mode mixing, thereby significantly enhancing decomposition efficiency and robustness [11-13].

The core principle of the VMD algorithm is to reformulate the signal decomposition problem into a non-recursive variational constraint optimization problem. The objective is to iteratively extract k modal components, $u_k(t)$, from the original signal, minimizing the cumulative bandwidth of these components while satisfying the conditions for signal reconstruction. Specifically, the VMD algorithm aims to minimize the following objective function:

$$\min_{\{u_k\}\{\omega_k\}} \sum_{k=1}^{K} \partial_t \left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right] e^{-j\omega_k t}{}_{2}^{2} \qquad (1)$$

Where:

$u_k(t)$…The k-th modal component;

ω_k …The central frequency of the k-th modal component;

∂_t…The time-domain derivative operator;

$\delta(t)$…The unit impulse function.

The optimization framework is further elaborated by incorporating Lagrange multipliers λ_k and a penalty factor α, thus formulating a variational problem. Ultimately, through iterative updates of the central frequencies and modal components, the signal's modal components are resolved [14-15].

2.1.2 FFT Transformation and Frequency Domain Feature Selection

2.1.2.1 FFT Transformation

FFT is an efficient algorithm for performing the DFT. It converts time-domain signals into frequency-domain signals, thereby enabling rapid analysis of spectral characteristics [16].

The primary operational steps of the FFT include the following components. Initially, the input vibration signal $x(t)$ is sampled to yield a discrete time-domain signal $x[n]$. Subsequently, the FFT algorithm is employed to transform this discrete time-domain signal into a frequency-domain signal $X[k]$, facilitating the acquisition of amplitude and phase information for different frequency components [17]. Based on this, spectral features can be further extracted, including the Magnitude Spectrum and PSD. The Magnitude Spectrum is utilized to characterize the energy distribution of the signal, and its computation is expressed by the formula:

$$|X[k]| = \sqrt{\mathrm{Re}(X[k])^2 + \mathrm{Im}(X[k])^2} \tag{2}$$

The PSD describes the power distribution across various frequencies. The formula for computing the PSD is as follows:

$$\mathrm{PSD}[k] = \frac{1}{N \cdot f_s} \cdot |X[k]|^2 . \tag{3}$$

Where:

N...The number of points in the FFT;

f_s...The sampling frequency;

$X[k]$...The FFT amplitude of the k-th frequency point.

The efficiency of FFT in computation and FE renders it an essential tool for analyzing the spectral properties of signals.

FFT translates the optimal modal component from the time domain to the frequency domain, calculating the signal's spectral characteristics. These spectral properties primarily include the Magnitude Spectrum and the PSD. Through these frequency domain features, the energy distribution of the signal at different frequencies can be revealed [18-20].

2.1.2.2 Frequency Domain Feature Selection

To reduce redundancy in frequency domain features, minimize the interference of irrelevant information, and enhance the model's ability to recognize key frequency components, the method of correlation coefficients is employed for feature selection, choosing components with the highest correlation with the original signal for feature combination.

Common correlation coefficient methods include Pearson correlation coefficient, Spearman's rank correlation coefficient, and Kendall's rank correlation coefficient. This study utilizes the Pearson correlation coefficient due to its simplicity, sensitivity to linear relationships, and effective measurement of trend consistency between the IMF and the original signal in the frequency domain, making it suitable for rapid selection of representative frequency domain features. The formula is as follows:

$$r = \frac{\mathrm{Cov}(u, x)}{\sqrt{\mathrm{Var}(u) \cdot \mathrm{Var}(x)}} . \tag{4}$$

Where:

r...The Pearson correlation coefficient, ranging from $[-1,1]$, with values closer to 1 indicating stronger correlation between the IMF component and the original signal;

$\mathrm{Cov}(u, x)$...The covariance, measuring the linear correlation between u (IMF component) and x (original signal) [21].

The process of selecting optimal frequency domain features using the correlation coefficient method is as follows: initially, the original signal is decomposed using VMD to obtain multiple IMF components; each IMF component is then transformed using FFT to extract its frequency domain features; subsequently, the Pearson correlation coefficient between each frequency domain feature and the original signal's spectrum is calculated, selecting the component with the highest correlation, thereby ensuring the retention of the most representative frequency information; finally, this component's spectral features are combined with the time-domain features obtained from VMD decomposition, to be used as input for subsequent models.

2.2 Fault Identification Module

This study presents an FD model for motor rotor systems, based on a CNN-BiGRU-Attention architecture, aimed at classifying faults. This model integrates CNN, BiGRU, and attention mechanisms to fully explore the spatio-temporal characteristics of bearing fault signals, thereby enhancing classification accuracy and generalization capabilities. The structure of the model is illustrated in Figure 2.

Initially, the CNN employs one-dimensional convolutions to extract local time-frequency features, combined with batch normalization and max pooling to reduce data dimensions and enhance feature representation capabilities. Subsequently, the BiGRU models short-term and long-term dependencies through bidirectional information flow, enabling the model to concurrently consider historical data and future trends, thus capturing temporal features more precisely. To further optimize FE, this study introduces an attention mechanism that adaptively adjusts weights to highlight critical features and reduce interference from redundant information, thereby improving the accuracy and robustness of the model's classification.

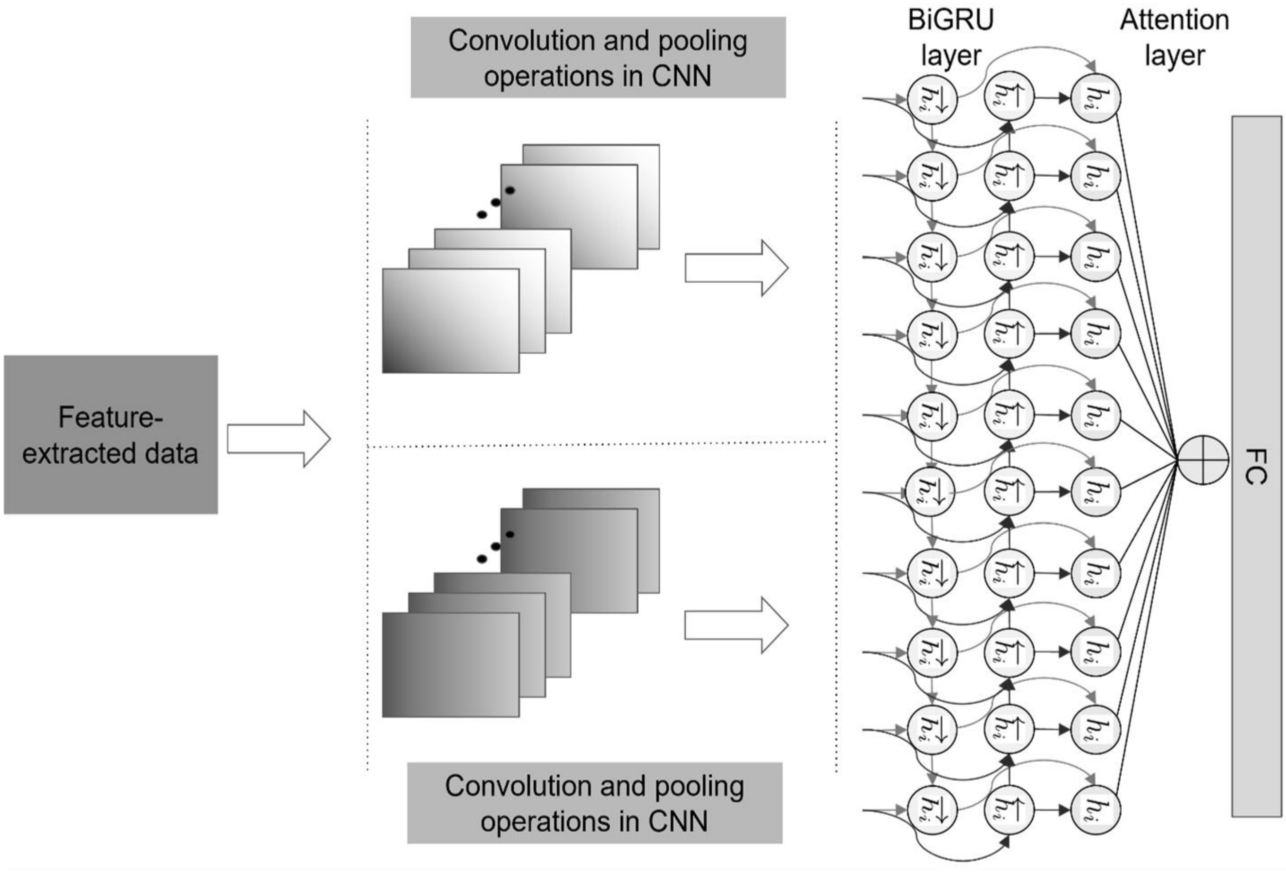

Fig. 2 *Structure of the CNN-BiGRU-Attention model*

3 Experimental Validation

To validate the feasibility of the aforementioned method, this study conducts experiments based on the rotor-bearing dataset provided by the Federal University of Brazil.

3.1 Dataset Description

The Machinery Fault Database (MAFAULDA) is a publicly available experimental dataset for FD in rotating machinery systems, developed by the Federal University of Brazil. The dataset contains vibration signals collected under various rotational speeds and load conditions, encapsulating multiple typical fault types such as imbalance, horizontal misalignment, and vertical misalignment. Each data file contains time-series vibration signals, suitable for time-domain, frequency-domain, and time-frequency domain analyses.

The dataset includes the normal state of the rotor system and nine fault states, with faults categorized according to the severity of the fault, as detailed in Table 1.

Tab. 1 *Rotor system fault types and labels*

Labels	Fault Types	Parameter	Fault Severity
1	Normal	0	
2	Imbalance	10g·cm	
3	Horizontal Misalignment	0.5mm	Mild Fault
4	Vertical Misalignment	0.51mm	
5	Imbalance	15g·cm	
6	Horizontal Misalignment	1.0mm	Moderate Fault
7	Vertical Misalignment	0.63mm	
8	Imbalance	20g·cm	
9	Horizontal Misalignment	1.5mm	Severe Fault
10	Vertical Misalignment	1.27mm	

Taking a mild fault in the rotor system as an example, the time-domain graph of its normal state and the normalized fault state are shown in Figure 3.

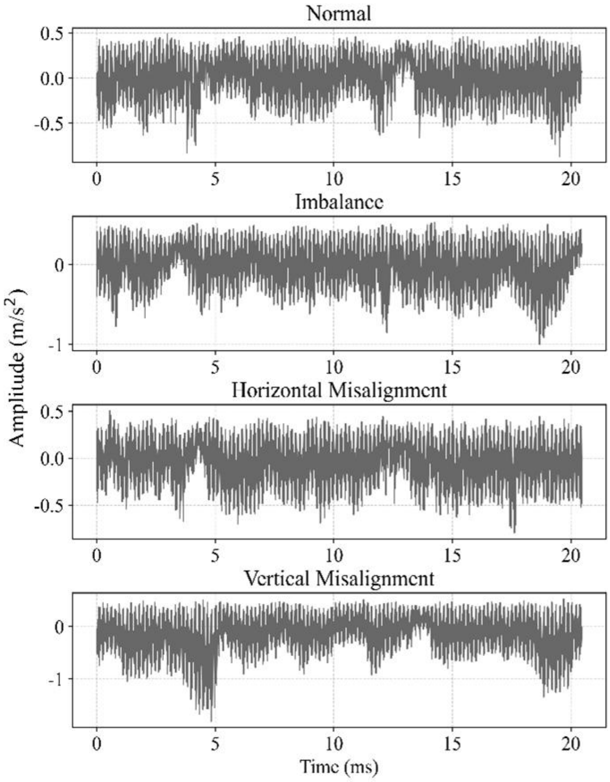

Fig. 3 *Time-domain signals of different states*

As observed from Figure 3, the time-domain signals of both normal and fault states are chaotic multi-component signals, making it challenging to classify faults from raw data. Hence, it is crucial to incorporate effective FE and denoising methods to extract key feature information, thereby enhancing the accuracy and robustness of FD in rotor systems.

3.2 Experiment on FE

3.2.1 Time-domain FE Based on VMD Decomposition

This section presents a case study using data from a mild unbalance fault, where the original signal is decomposed using VMD, resulting in various modal components. The time-domain representation of these components is illustrated in Figure 4.

As depicted in Figure 4, the original signal comprises multiple frequency components and is subject to substantial noise interference, manifesting as a complex mixed signal. After decomposition, the IMFs from IMF1 to IMF4 are obtained, each reflecting the time-domain characteristics of different frequency bands: IMF1 predominantly represents low-frequency time-domain features with a gentle amplitude, likely indicating trend information of the signal; IMF2 encompasses mid-frequency features, exhibiting more pronounced oscillations; IMF3 increases in frequency, reflecting mid-to-high frequency time-domain features and possibly containing impulse information; IMF4, with the highest amplitude and frequency, displays complex high-frequency characteristics and serves as the primary carrier of the original signal's time-domain features. Collectively, the IMFs effectively segregate the time-domain components of the original signal across different frequencies, reducing band overlap, and providing a reliable foundation for subsequent frequency domain analysis and FD.

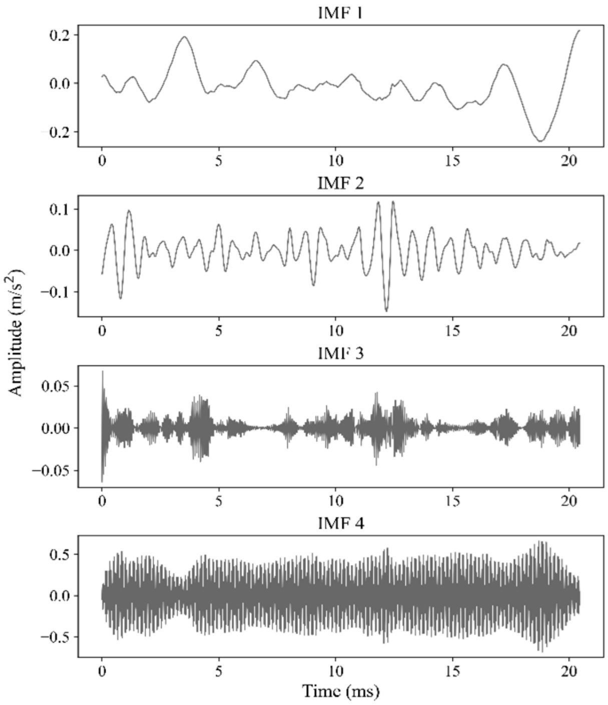

Fig. 4 *Time-domain graph of VMD decomposition for mild unbalance fault data*

3.2.2 Extraction and Selection of Frequency-domain Features

Following the VMD decomposition, an FFT is applied to all component signals to obtain their frequency-domain features. The frequency-domain graph of the mild unbalance fault data is shown in Figure 5.

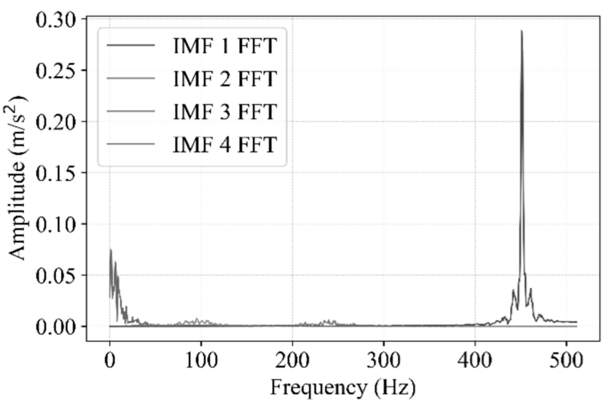

Fig. 5 *Frequency-domain graph of FFT transformed components*

As Figure 5 reveals, the spectrum of the original signal, post-VMD decomposition, is partitioned into four IMFs, each IMF's FFT spectrum corresponding to the energy distribution characteristics of different frequency bands. The energy of IMF1 is mainly concentrated in the low-frequency area (0–50 Hz), while IMF2 and IMF3 cover mid-to-low frequency bands, with their energy distribution being relatively dispersed and significant spectral amplitudes still present around 100 Hz and 240 Hz, indicating these modes carry mid-frequency feature information. Notably, IMF4 prominently generates a peak in the high-frequency area (around 450 Hz), underscoring its role in encompassing the high-frequency components of the original signal.

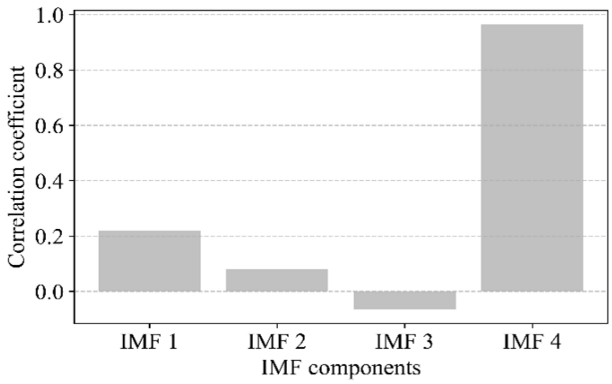

Fig. 6 *Correlation coefficients of IMF components*

To enhance the efficacy of feature representation and reduce the complexity of model training, this study adopts the correlation coefficient method to filter frequency-domain features. This strategy effectively minimizes redundant frequency-domain information, controls feature dimensions, and enhances the correlation between the features and the original signal, thereby improving the model's recognition accuracy and generalization capabilities.

The Pearson correlation coefficients calculated for the FFT-transformed IMF components are displayed in Figure 6.

Figure 6 indicates that IMF1, IMF2, and IMF3 exhibit low correlation, suggesting their minor compositional presence in the signal. Based on this correlational analysis, IMF4 is identified as the optimal choice for FE and FD. Consequently, this frequency-domain feature is combined with the time-domain features obtained from VMD decomposition to form a multi-channel feature matrix.

3.3 Fault Identification Based on CNN-BiGRU-Attention Model

In order to explore the superiority of the CNN-BiGRU-Attention deep learning model proposed in this study, a comparative analysis was conducted with several baseline models including the one-dimensional Convolutional Neural Network (1D-CNN), two-dimensional Convolutional Neural Network (2D-CNN), LSTM, CNN-BiGRU, and CNN-LSTM.

The experiments were performed in a VScode environment, with the specific configuration settings of the CNN-BiGRU-Attention model presented in Table 2.

Tab. 2 *Structural and parameter configuration of the CNN-BiGRU-Attention network model*

No.	Model name	Parameters of The Model	Size of Output	Activation Function
1	Conv1D_1	5→32,kernel_size=3,padding=1	32×32×1024	ReLU
2	BatchNorm_1	32	32×32×1024	-
3	MaxPooling_1	kernel_size=2,stride=2	32×32×512	-
4	Conv1D_2	32→64,kernel_size=3,padding=1	32×64×512	ReLU
5	BatchNorm_2	64	32×64×512	-
6	MaxPooling_2	kernel_size=2,stride=2	32×64×256	-
7	Conv1D_3	64→128,kernel_size=3,padding=1	32×128×256	ReLU
8	BatchNorm_3	128	32×128×256	-
9	MaxPooling_3	kernel_size=2,stride=2	32×128×128	-
10	BiGRU_1	128→128,bidirectional=True	32×128×256	Tanh
11	BiGRU_2	256→64,bidirectional=True	32×128×128	Tanh
12	Attention	-	32×1×128	-
13	Linear_1	128→64	32×1×64	ReLU
14	Dropout	p=0.1	32×1×64	-
15	Linear_2	64→10	32×1×10	-

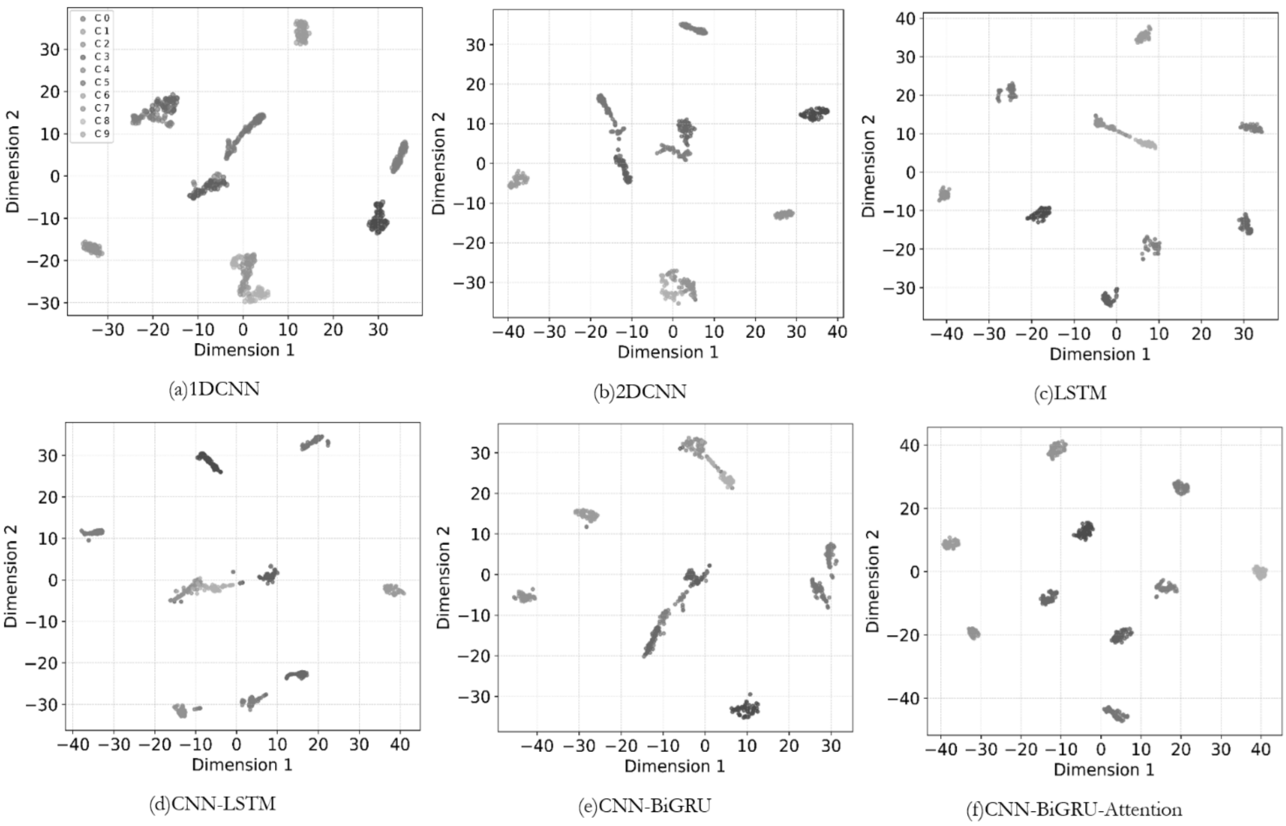

***Fig. 7** t-SNE feature distribution maps of various models*

After the decomposition via VMD and transformation through FFT, the resulting multi-feature matrix was divided into training, validation, and test sets in a 7:2:1 ratio. The t-SNE feature distribution maps for each model are shown in Figure 7.

From the t-SNE feature distribution maps illustrated in Figure 7, it can be observed that 1D-CNN and 2D-CNN primarily rely on local FE. Although they are capable of learning certain time-frequency features, there remains a significant overlap in features across different categories, resulting in lower discriminability. LSTM and CNN-LSTM enhance feature clustering through temporal modeling, but some category boundaries remain indistinct, particularly under complex operational conditions where they are susceptible to noise interference. In contrast, CNN-BiGRU, by incorporating bidirectional GRU, not only enhances temporal feature learning but also facilitates greater separation among category features, thereby improving classification stability. Further incorporation of the attention mechanism in the CNN-BiGRU-Attention model effectively concentrates on critical feature regions, significantly enhancing the ability to distinguish between categories. This results in more compact feature distributions and clearer boundaries between categories, ultimately achieving optimal feature clustering. These results validate that the FE paired with the attention mechanism in the CNN-BiGRU-Attention model can fully explore the time-frequency characteristics of fault signals, thereby enhancing the accuracy and robustness of rotor system fault classification.

Further calculations of the fault classification confusion matrices for each model are shown in Figure 8.

As indicated in Figure 8, where C1 to C10 correspond to the fault types listed in Table 2, the CNN-BiGRU-Attention model demonstrates superior performance in fault classification tasks. It exhibits stronger FE and discriminative capabilities; across all categories, it achieves higher accuracy rates, particularly in complex fault conditions such as C8 and C9, where it shows the lowest misclassification rates, thus displaying robust performance. In comparison, 1D-CNN and 2D-CNN have certain misjudgments under complex patterns, and while LSTM has temporal modeling capabilities, its overall accuracy does not match that of the hybrid models. Both CNN-LSTM and CNN-BiGRU show stable performance across multiple categories, but they are outperformed by the CNN-BiGRU-Attention model, which can focus on critical feature areas and effectively elevate classification performance under complex operational conditions.

To comprehensively assess the performance of the models, further calculations of performance metrics for each model were undertaken, with the results presented in Table 3.

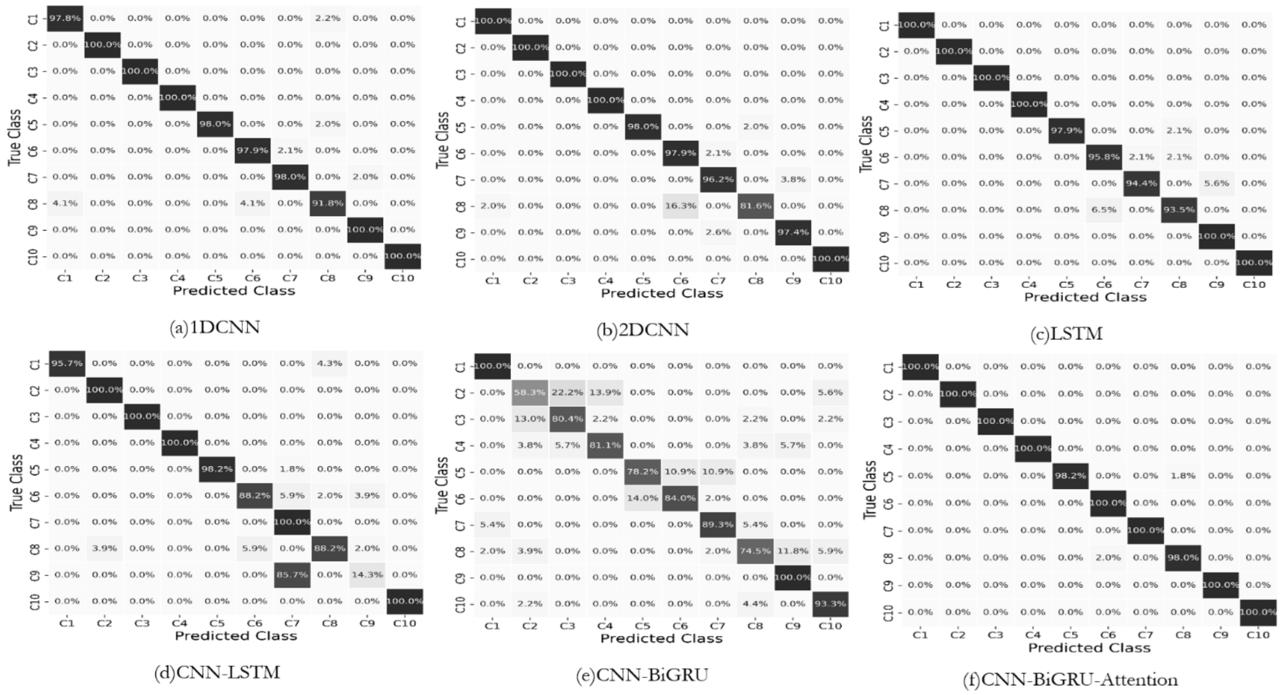

***Fig. 8** Confusion matrices of fault classification for various models*

***Tab. 3** Performance metrics of various FD models*

Model	Accuracy	Precision	Recall	F1	Kappa Coefficients	Jaccard Coefficients
1DCNN	0.9888	0.9893	0.9897	0.9894	0.9876	0.9793
2DCNN	0.9710	0.9735	0.9725	0.9721	0.9677	0.9478
LSTM	0.9799	0.9798	0.9821	0.9808	0.9776	0.9630
CNN-LSTM	0.8938	0.9069	0.8846	0.729	0.8815	0.8266
CNN-BiGRU	0.8438	0.8370	0.8421	0.8377	0.8262	0.7302
The Proposed Model	0.9958	0.9961	0.9963	0.9962	0.9954	0.9924

Table 3 demonstrates that the CNN-BiGRU-Attention model outperforms in all performance metrics, particularly excelling in accuracy (99.58%), precision (99.61%), and F1-score (99.63%), all of which approach the maximum achievable values. The 1D-CNN and 2D-CNN models also perform commendably but are slightly inferior to the CNN-BiGRU-Attention model. In contrast, the CNN-LSTM and CNN-BiGRU models exhibit lower performance, especially in terms of F1-score and Jaccard index. Overall, the CNN-BiGRU-Attention model exhibits the most optimal comprehensive performance in this task.

4 Conclusion

To ensure the efficiency and accuracy of the FD system for electric motor rotor systems, this study proposes an FD method for electric motors based on FE and the CNN-BiGRU-Attention model, with the following main conclusions:

- 1) Utilizing VMD to decompose electric motor fault signals, combined with FFT for frequency domain FE, effectively eliminates noise and redundant information from the signals, providing high-quality signal inputs for subsequent fault classification.
- 2) The FE capabilities of the CNN-BiGRU model, enhanced by the attention mechanism, allow the model to automatically focus on critical features within the fault signals. This extraction of representative fault information enhances the discriminative ability of the features and increases the robustness of the model.
- 3) The CNN-BiGRU-Attention model proposed in this study surpasses a 99% threshold in all metrics, particularly excelling in accuracy, precision, and F1-score. It significantly outperforms other FD models such as 1D-CNN, 2D-CNN, LSTM, CNN-LSTM, and CNN-BiGRU, establishing its superior classification effectiveness.

Acknowledgement

This work was supported by National Natural Science Foundation of China under Grant 52374154.

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