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# Advanced Multidimensional Vibration Signal Processing for Gearbox Pitting Fault Classification using IMPE, STFT, and a CNN-Driven Deep Learning Approach

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**Abstract**

Gearbox fault diagnosis is crucial for ensuring the reliability and efficiency of industrial machinery. This study proposes a novel approach by analyzing multidimensional vibration signals under varying load conditions (0Nm to 30Nm) to enhance pitting fault classification accuracy. The vibration signals were decomposed into Multidimensional Intrinsic Mode Functions (IMFs) using Noise-Assisted Multivariate Empirical Mode Decomposition (NA-MEMD), allowing for a more detailed representation of fault-induced vibrations. To select the most informative IMFs, Improved Multiscale Permutation Entropy (IMPE) with a standard deviation-based thresholding method was applied, ensuring the retention of relevant features. For time-frequency analysis, the Short-Time Fourier Transform (STFT) was used to generate heat maps, providing insights into the transient behaviour of faults. From the Time-Frequency Representation (TFR), the Z-axis was identified as the most sensitive to fault-related vibrations, making it the optimal direction for classification. A deep learning-based classification framework was then developed to distinguish between healthy and faulty gearbox conditions, leveraging Convolutional Neural Networks (CNNs) for automated feature extraction and classification. Furthermore, the proposed method was benchmarked against established deep learning architectures, VGG16 and ResNet-50, to evaluate its performance. By integrating multidimensional vibration analysis, entropy-based feature selection, and deep learning, this research establishes a robust and efficient fault diagnosis framework. The findings highlight the importance of multidimensional signal processing in predictive maintenance, providing a foundation for more reliable gearbox condition monitoring in industrial applications.

*Keywords*: "Multidimensional Vibration signal", "NA-MEMD", "IMPE", "STFT", "Deep learning approach", "Fault classification".

## 1. Introduction

Gears are essential components in industrial systems, enabling precise torque transmission and speed regulation. However, challenging operational conditions often result in various mechanical faults, including wear, pitting, fractures, surface fatigue, and tooth breakage. Among these, pitting is particularly problematic due to its subtle onset and the severe mechanical failures that can arise if left undetected. This failure mode is primarily induced by excessive stress from factors such as gear misalignment and high-load transmission. Industry standards define hardened gear failure as occurring when pitting affects 0.5% of the total active tooth flank area or 4% of an individual active tooth flank (Li et al., 2020). Given its critical impact on machinery performance, pitting detection and diagnosis remain key research areas. The adoption of advanced gearbox condition monitoring techniques is instrumental in identifying potential faults at an early stage, preventing catastrophic failures, and ensuring the uninterrupted operation of industrial systems (Alper et al., 2023;). The detection of gearbox faults typically involves the use of condition monitoring techniques such as thermography, oil analysis, acoustic emission, and vibration analysis(Goswami & Nandan Rai, 2023). In gearbox condition monitoring, vibration signals collected from multiple sensors undergo decomposition into Intrinsic Mode Functions (IMFs) using methods such as EMD, EEMD, CEEMD, MEMD, and NA-MEMD. While traditional univariate methods (EMD, EEMD, CEEMD) analyze each signal in isolation, they inherently neglect inter-signal dependencies, which may limit the effectiveness of fault detection. MEMD and NA-MEMD address this limitation by decomposing multi-channel signals collectively, preserving inter-signal relationships and offering deeper insight into fault dynamics. Moreover, NA-MEMD exhibits enhanced noise suppression capabilities compared to MEMD, further refining fault detection accuracy in complex gearbox systems (Ahrabian et al., 2012; Rehman & Mandic, 2010; Xu et al., 2022). To diagnose pitting faults, researchers have applied time-domain features, EMD, FFT, and STFT, primarily analyzing single vibration signals. However, industrial applications often involve multi-sensor setups where single-signal analysis may fail to capture inter-signal correlations, potentially limiting the effectiveness of fault detection and necessitating more advanced multi-sensor diagnostic strategies (Sánchez et al., 2018) (Häderle et al., 2024)(Happi et al., 2023). To address this issue, this study employs NA-MEMD to generate multidimensional IMFs, facilitating an advanced multidimensional analysis of pitting faults in gear systems.

In gearbox fault diagnosis, Short-Time Fourier Transform (STFT) is widely used for time-frequency analysis. Unlike the Fourier Transform, which provides only frequency data, STFT reveals frequency variations over time, improving fault detection (Benkedjouh et al., 2018; Happi et al., 2023). Applying the STFT to vibration data decomposes the signal into localized frequency components over time, generating a spectrogram. This spectrogram represents the signal as an image, where colour intensity corresponds to amplitude variations across frequencies and time. Such a transformation enables deep learning models, particularly Convolutional Neural Networks (CNNs), to extract meaningful vibration features for precise fault detection and classification(Joseph et al., 2024; Lee et al., 2023).

Convolutional Neural Networks (CNNs) have emerged as a powerful deep learning framework, achieving remarkable success in various fields, including image recognition, facial recognition, handwriting analysis, action recognition, material classification, and speech processing(Guo et al., 2018;). A key advantage of CNNs in image recognition is their ability to process raw image data directly, minimizing the need for complex pre-processing. This efficiency is attributed to CNNs' unique architecture, which employs local weight sharing to enhance feature extraction. Additionally, CNNs have demonstrated significant potential in medical diagnostics(Zhao & Jia, 2016), showcasing their strength in analyzing both images and multivariate time-series data(Navathe et al., 2016). This highlights their capability for advanced diagnostic and prognostic applications. Despite these advantages, CNNs remain underutilized in the fault diagnosis of mechanical systems, presenting an opportunity for further exploration in industrial applications. CNNs perform image classification by autonomously extracting relevant features. Unlike traditional methods that necessitate manual feature computation and selection for condition classification, CNNs enable the development of learning models without human intervention. Essentially, when an image encapsulates vibration signal characteristics—such as frequency components, amplitude, and sensor positioning—the CNN model can independently compute these features, ensuring consistent and reliable classification(Joseph et al., 2024; Lee et al., 2023).

The literature reveals a critical gap in leveraging multivariate signal analysis and image-based processing for pitting fault diagnosis in gearboxes. Most methods focus on univariate data, ignoring multi-dimensional sensor correlations crucial for accurate fault detection. While spectrogram-based deep learning aids fault classification, its application to multidimensional vibration signals for pitting detection remains underexplored. Bridging this gap could significantly improve diagnostic accuracy and system reliability.

In this study, NA-MEMD is employed to decompose multidimensional vibration signals into Multidimensional Intrinsic Mode Functions (IMFs) obtained from experimental data. Improved Multiscale Permutation Entropy (IMPE) is then applied to identify the most effective IMFs in each direction. Subsequently, the STFT is performed on these selected IMFs to extract time-frequency representations and generate corresponding 2D spectrogram images. Finally, the most relevant fault axis is determined, and fault classification is conducted using the proposed Convolutional Neural Network (CNN) model.

This paper is structured as follows: Section 2 delves into the fundamental technical aspects, setting the groundwork for the study. Section 3 introduces the proposed methodology, detailing the approach taken. Section 4 presents a comprehensive analysis of the results, accompanied by a critical discussion. Finally, Section 5 encapsulates the key findings and conclusions of the research.

## 2. Theoretical background

### 2.1 NA-*MEMD*

The strategy of augmenting data processing with additional noise channels for enhanced performance is known as noise-assisted multivariate empirical mode decomposition (NA-MEMD). With modal alignment and its behaviour as a dyadic filter-bank in the presence of white Gaussian noise, the MEMD algorithm benefits from the noise channels, which serve as a reference in the time-frequency space, helping to achieve more precise IMF estimates and enhancing the time-frequency analysis. The NA-MEMD algorithm follows a structured six-step process as outlined in the reference (Zhang et al., 2017, 2021).

### 2.2 *Improved MPE*

As a widely adopted complexity metric, Permutation Entropy (PE) quantifies the irregularity of time series data by assessing ordinal pattern distributions. However, its single-scale computation restricts its ability to capture hierarchical signal characteristics, making it prone to noise interference and limiting its resolution in detecting subtle changes. Multiscale Permutation Entropy (MPE) expands PE by integrating multiple time scales via a coarse-graining approach, albeit with the drawback of potential information loss. Improved Multiscale Permutation Entropy (IMPE) further advances MPE by optimizing entropy computation, increasing its sensitivity to structural complexity and fault identification. This enhancement makes IMPE a robust methodology for gearbox vibration analysis and predictive maintenance. The detailed procedure for computing Improved Multiscale Permutation Entropy (IMPE) can be referenced from (Azami & Escudero, 2016). For consistency and clarity, we have strictly adhered to the notation and methodology presented in the referenced study (Azami & Escudero, 2016). The IMPE can be computed by Equation (1);

$$\mathrm{IMPE}(x,\tau,d)=\frac{1}{\tau}\sum_{i=1}^{\tau}\mathrm{PE}\left(z_i^{(\tau)}\right) \tag{1}$$

### 2.3 *Short-Time Fourier Transform (STFT)*

The Short-Time Fourier Transform (STFT) is used to analyse vibration signals in the time-frequency domain, helping detect fault characteristics. It is defined by Equation (2) as:

$$X(n,f)=\sum_{n=-\infty}^{\infty}x(n+m)w(m)e^{-i\frac{2\pi fm}{N}} \tag{2}$$

where $w(m)$ is the window function. The resulting spectrogram provides a visual representation of frequency variations over time, aiding in fault diagnosis. By applying the window function $w(m)$ the time-domain signal $x(n)$ is divided into segments, enabling FFT analysis across NNN samples(Joseph et al., 2024).

### 2.4 *Proposed CNN*

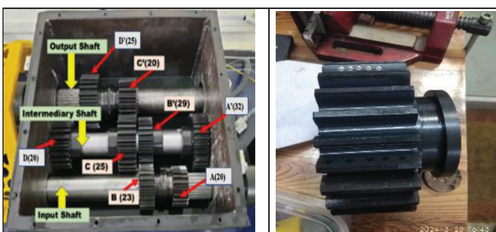
Convolutional Neural Networks (CNNs) are widely used for feature extraction and classification in image-based fault diagnosis due to their ability to capture spatial hierarchies. The proposed CNN model is designed to achieve an optimal balance between computational efficiency and classification accuracy. Table 1 represent the Proposed CNN model and the comparison of proposed model with other.

**Table 1** Parameter of Proposed CNN and comparing Deep leaning model

| Component | VGG16 | ResNet-50 | Proposed CNN |
|---|---|---|---|
| Number of Layers | 16 | 50 | 10 |
| Convolutional Filters | 3×3 Filters | 3×3 Filters & Skip Connection | 3×3 Filters |
| Activation Function | ReLU | ReLU | ReLU |
| Pooling | Max Poolin g | Max Pooling | Max Pooling |
| Skip Connections | No | Yes | No |
| Dropout | No | No | Yes |
| Parameter Count | ~138M | ~25M | ~1M |
| Optimizer | SGD | Adam | Adam |
| Data Augmentation | No | No | Yes |

## 3. Experiment Setup and Proposed Methodology

The study analysed gearbox performance under healthy and faulty conditions (broken tooth and pitted gear) at torque levels of 0, 10, 20, and 30 Nm. An experimental setup shown in Figure 1 at IIT Kharagpur featured a 2-stage, 4-speed spur gearbox, monitored using vibration, oil, and sound analysis. A tri-axial accelerometer at 1000 RPM recorded vibration data at a sampling rate of 20,000 points/second from the AA'-DD' gear interface for 5 second. Faults included a pitting in DD', enabling detailed analysis of multidimensional vibration signals for fault classification.




(a) (b)

**Figure 1** (a) Multi-stage speed reducer gearbox (b) Pitting fault

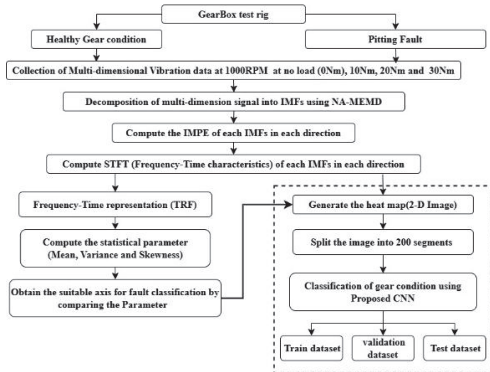



**Figure 2** Proposed Methodology

Figure 2 presents the proposed methodology used in the paper. The multidimensional raw vibration data underwent decomposition through NA-MEMD, yielding a series of IMFs for each loading condition along each axis. Subsequently, the IMPE of each IMF was computed. To establish a selection criterion, the standard deviation of the IMPE values was determined, and IMFs with IMPE values exceeding this threshold were retained for reconstruction. This selection process ensured that a single effective IMF was extracted for each axis under each loading condition, facilitating a more precise characterization of the respective gear condition. After obtaining the effective IMF along each axis, the effective IMF was analysed using the Short-Time Fourier Transform (STFT) for each axis, which provides a time-frequency representation (TFR) of the signal. STFT involves segmenting the signal into overlapping time windows and computing the Fourier Transform within each window, thereby capturing the variation of dominant frequency components over time. Upon identifying the most significant axis, STFT is used to process the effective IMF, resulting in a heat map. This heat map is subsequently sectioned into 200 parts, after which the proposed CNN architecture is deployed for fault classification.

## 4. Result and Discussion

Multidimensional vibration data is acquired from the gearbox test setup under various loading conditions and subsequently decomposed into multidimensional IMFs using NA-MEMD. Figure 3 illustrates the original vibration signal along with its corresponding IMFs along each axis, extracted via NA-MEMD for 20Nm at 1000 RPM.

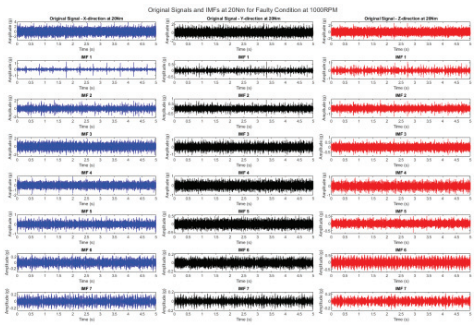



**Figure 3** Original Multidimensional vibration signal and Multidimensional IMFs along x, y and z axis.

Following the generation of multidimensional IMFs, the IMPE value for each IMF is calculated per axis using Equation (1). The prescribed parameters for the IMPE calculation include an embedding dimension of 4, a time delay of 2, and a scale factor of 5. Figure 4 shows the IMPE values of IMFs along z-axis at 20Nm for faulty gear condition, similarly at 20Nm the IMPE values for x and y axis were also computed. The standard deviation of IMPE is computed after determining the IMPE for each IMF along a particular axis. IMFs with IMPE values above this threshold are reconstructed to obtain the Effective IMF. This process results in three Effective IMFs for every gear condition at a given loading condition.

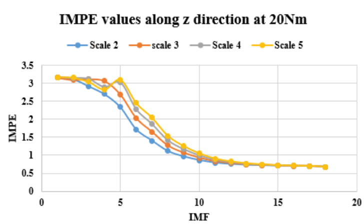



**Figure 4** IMPE values of IMFs along z-axis at 20Nm for faulty gear condition

Following the selection of the optimal effective IMF, TFR analysis is performed to extract meaningful fault-characteristics. The effective IMF is processed through STFT to obtain the corresponding TFR plot, facilitating condition monitoring. Figure 5,Figure 6 and Figure 7 illustrates the TFR for the x, y and z-axis respectively under various load conditions. The time-frequency representation (TFR) analysis of faulty gearbox vibration data across different load conditions (0Nm, 10Nm, 20Nm, and 30Nm) reveals key insights into fault-induced signal characteristics.

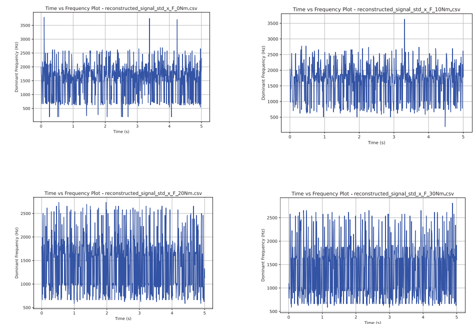


**Figure 5** TFR of Effective IMF for x axis (a) 0Nm (b) 10Nm (c) 20Nm (d) 30Nm

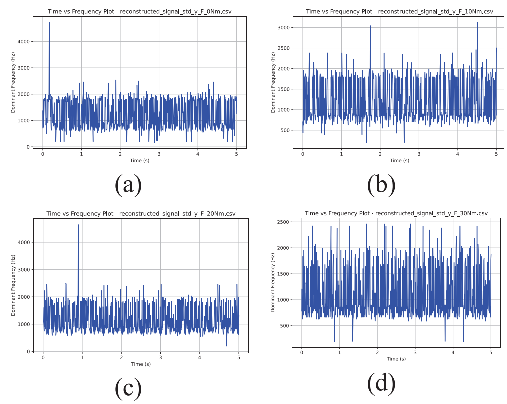



**Figure 6** TFR of Effective IMF for y axis (a) 0Nm (b) 10Nm (c) 20Nm (d) 30Nm

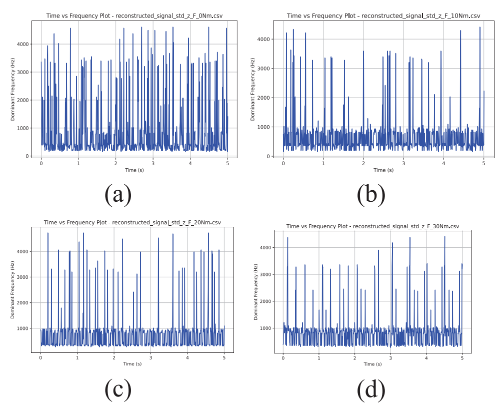
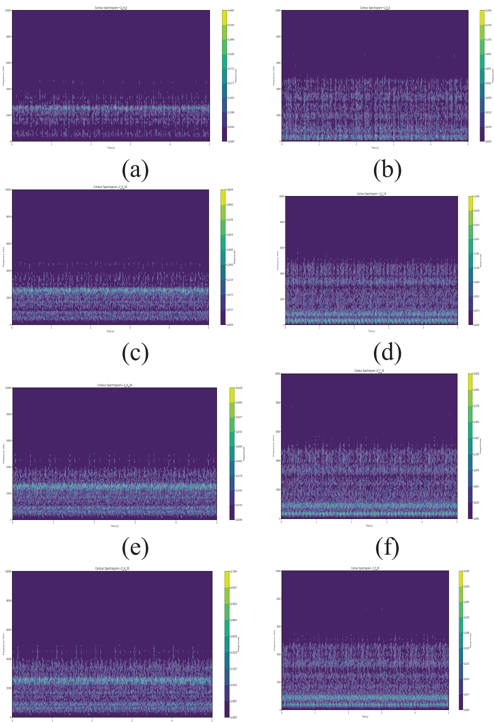



**Figure 7** TFR of Effective IMF for z axis (a) 0Nm (b) 10Nm (c) 20Nm (d) 30Nm

The variations in frequency distribution with changing load conditions suggest that fault characteristics evolve with torque, emphasizing the necessity for load-dependent fault diagnosis techniques. From the Figure 5, Figure 6 and Figure 7 it is shown that the in the z-axis. The TFR of the effective IMF in the z-axis across varying load conditions (0Nm, 10Nm, 20Nm, and 30Nm) demonstrates its superiority in fault characterization. The z-axis exhibits a higher density of transient peaks, with a significantly greater frequency component concentration compared to the x and y axes. This suggests that fault-induced vibrations predominantly manifest in the z-direction, making it the most responsive axis for fault detection.

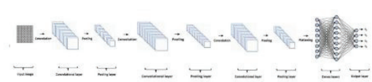


(a) (b) (c) (d) (e) (f) (g) (h)

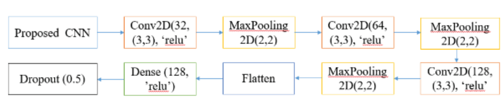
**Figure 8** Heat Map of effective IMF of z axis (a) Healthy at 0Nm (b) Faulty at 0Nm (c) Healthy at 10Nm (d) Faulty at 10Nm (e) Healthy at 20Nm (f) Faulty at 20Nm (g) Healthy at 30Nm (h) Faulty at 30Nm

The observed fluctuations in frequency intensity indicate pronounced non-stationary behaviour, likely resulting from the impulsive nature of gear pitting faults. Moreover, the consistently elevated peak intensities in the z-axis further underscore its diagnostic relevance. The progressive increase in peak occurrences with load suggests that the fault signature amplifies under higher operational stresses. These findings establish the z-axis as the most sensitive and reliable axis for detecting gearbox faults, making it the preferred direction for vibration-based fault diagnosis.

After selecting the optimal axis, the next essential step is to classify the gear condition as either healthy or faulty. This classification is performed by generating heatmaps of the effective IMF along the z-axis for each loading condition under both gear conditions. Figure 9 show the heat map healthy and faulty gear at different loading condition. The heat map clearly illustrates that the frequency components in the faulty condition exhibit a significant increase compared to the healthy state. This heightened frequency response indicates the presence of fault-induced vibrations, reinforcing the effectiveness of the proposed model in distinguishing between healthy and faulty conditions. The observed increase in frequency intensity highlights the model's capability to accurately capture fault signatures, demonstrating its robustness in gearbox pitting fault diagnosis. Furthermore, for classification each heatmap is systematically divided into 200 segments. For instance, under a 20Nm load in the faulty condition, the heatmap is split into 200 segments, and this segmentation process is applied to all conditions. As a result, a total of 1,600 heatmap segments are obtained across the two gear conditions and four loading levels. These segments are then used as input for the proposed CNN model, which is responsible for distinguishing between healthy and faulty gear conditions. Figure 9 presents the structure of the CNN, while its architecture and parameter details are elaborated in section 2.4.



(a)




(b)

**Figure 9** Architecture of Proposed CNN

For fault classification, the 1600 data segments are systematically divided into three subsets: the training dataset, validation dataset, and testing dataset. 70% of the data is allocated for training to ensure the model learns the underlying patterns effectively. 20% of the data is used for validation, allowing fine-tuning of hyperparameters and preventing overfitting. Finally, 10% of the data is reserved for testing, providing an unbiased evaluation of the model's performance in classifying faults accurately.

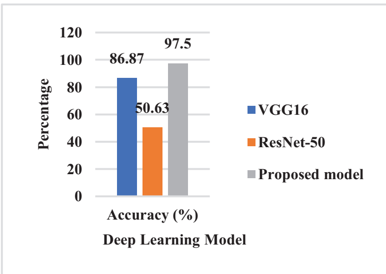



**Figure 10** Classification test accuracy

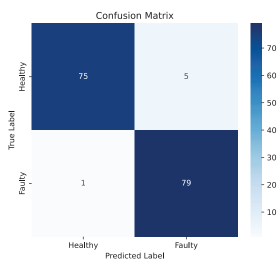



**Figure 11** Confusion matrix

Figure 11 presents the confusion matrix for the proposed Convolutional Neural Network (CNN), illustrating the model's classification performance in fault diagnosis. To further validate the effectiveness of the proposed CNN, it is also evaluated against VGG16 and ResNet-50, two well-established deep learning architectures. The hyperparameters and configurations used for these deep learning models are detailed in Table 1, ensuring a fair comparison. This evaluation highlights the robustness of the proposed model in distinguishing fault conditions and its comparative performance against state-of-the-art architectures. The proposed model in Figure 10 achieved 96.25% accuracy, surpassing VGG16 and ResNet-50 in fault classification. Its superior performance highlights its effectiveness in extracting fault features from vibration signals, ensuring precise and reliable fault diagnosis for industrial applications.

## 5. Conclusion

This study presents an advanced gearbox fault diagnosis framework utilizing multidimensional vibration analysis, entropy-based feature selection, and deep learning. Unlike traditional approaches that rely on single-axis data, this method decomposes vibration signals from all three axes using NA-MEMD, preserving essential fault-related features. The selection of effective IMFs using IMPE and standard deviation-based thresholding ensures that only the most relevant components contribute to fault characterization. The STFT-based TFR analysis revealed that the Z-axis exhibits the highest sensitivity to fault-induced vibrations, making it the most informative direction for classification.

To enhance fault detection accuracy, a CNN-based classification model was developed and compared with VGG16 and ResNet-50. The proposed model achieved an impressive classification accuracy of 96.25%, significantly outperforming VGG16 (86.87%) and ResNet-50 (50.63%). This superior performance underscores the effectiveness of the proposed approach in capturing fault characteristics with high precision. The improved accuracy is attributed to the model’s ability to extract relevant features from multidimensional vibration signals, leading to more reliable classification results.

By integrating advanced signal decomposition, entropy-based feature selection, and deep learning-based classification, this study establishes a highly efficient and robust fault diagnosis framework for gearbox monitoring. The results emphasize the importance of multidimensional vibration analysis in predictive maintenance, providing an effective solution for early fault detection in industrial gearboxes.

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