

Faultformer: A CNN–transformer Multi-domain Feature Fusion Network for Intelligent Bearing Fault Diagnosis

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FAULTFORMER: A CNN–TRANSFORMER MULTI-DOMAIN FEATURE FUSION NETWORK FOR INTELLIGENT BEARING FAULT DIAGNOSIS

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Abstract

In this paper, FaultFormer is proposed as a new hybrid intelligent mechanism to automatically diagnose rolling bearing faults with vibration signals in an induction motor. It combines multi-domain feature fusion based on handcrafted statistical features, frequency-domain analysis and deep features learned through a hybrid CNN–Transformer–based approach. Whereas CNN layers capture local temporal vibration patterns, the Transformer encoder leverages multi-head self-attention to capture long-range temporal dependencies that are important for identifying periodic mechanical faults. The framework was validated using the Case Western Reserve University (CWRU) bearing dataset covering ten fault categories in different load modes and defect severities. Experimental outputs show that the model reaches 99.98% classification mean accuracy when the model was executed 20 times, with a precision of 99.68%, a recall of 99.68%, and 99.80% F1-score, outperforming some of the newly introduced state-of-the-art deep learning and hybrid models. This integrated approach to feature fusion successfully represents global signal patterns with localised transient features, providing a robust, repeatable approach to the analysis of industrial machine condition.

Keywords - Bearing Fault Diagnosis, FaultFormer-Net, CNN–Transformer, Multi-Domain Feature Fusion, Induction Motor, vibration analysis, Time–Frequency Feature Extraction.

1. INTRODUCTION

Early recognition and identification of motor faults, which can be broadly segmented into mechanical and electrical, is essential in order to guarantee the reliability and economic operation of the motor. Common fault

detection and diagnosis (FDD) techniques are commonly divided into three different paradigms: signal-based, model-based, and knowledge-based paradigms. Model-based techniques are exploited to produce analytical representations developed from physical principles and system identification, but they will become less and less viable with the growing complexity of systems. By contrast, signal-based methodologies focus on the measurement of many, various, measurable quantities - such as vibration, motor current, rotational speed and temperature - to find and characterise the fault. Popular signal processing methods used in detection of electrical machinery fault detection include spectral estimation [1-2], wavelet transformation and wavelet packet decomposition [6-8], time-frequency analysis [3], fast Fourier transform (FFT) [4-6], scale-invariant feature transform (SIFT) [7], and sequence analysis [8]. These approaches rely on advanced signal processing frameworks to be able to generate salient features from the raw data, which help in determining the anomalies associated with the problem (i.e., bearing defects).

Unlike the classical methodologies, data-driven condition monitoring schemes build on the high data content that is collected from advanced sensing, data acquisition, and control systems. In this domain, shallow machine learning models have been shown to be capable of detecting and diagnosing fault-specific motor current signals [9]. However, they often use features crafted by hand, and diverse classifiers, frequently fed short data sets of specific motors or rotating machinery (RM). Therefore, their usability is limited, and their performance declines with a variety of system types, fault states or larger datasets, which makes developing a universal diagnosis system quite difficult. An excellent example of this limitation is the presence of variability in fault detection for machines powered by adjustable speed drives (ASDs) that operate under varying speeds, adding the challenge of robust fault diagnosis.

2. RELATED WORK

Feature extraction is an important aspect of fault diagnosis in that it is used to identify and describe informative patterns from raw data, e.g. vibration signals, to make fault diagnosis more accurate. Traditional feature extraction methods, such as Empirical Mode Decomposition (EMD), symbolic aggregate approximation (SAX), and multifractal analysis, have been widely used in the domain of rotating machinery diagnostics. For example, [10] introduced the EMD-based method, based on which extracted features were proposed to intelligently find the faults for the rotating mechanism using a non-naive Bayesian classifier. Similarly, [11] used a symbolic aggregate approximation framework to extract features from bearing vibration signals and categorise the features with the nearest neighbour algorithm. [12] showed that bearing vibration signals have multifractal characteristics, and they motivated researchers to utilise multifractal detrended fluctuation analysis to extract features for proactive fault detection. Additionally, [13] proposed to alleviate the drawbacks of the classical Fourier-based methodologies, through continuous wavelet transform (CWT) for signal, including Support Vector Machines (SVM) for fault classification.

Traditional feature extraction methods have been successful at fault diagnosis. Currently, these methods largely use shallow learning approaches, which have their own limitations. Methods like Bayesian classifiers, nearest-neighbour methods, and support vector machines (SVMs) require manual feature engineering. Because we need this knowledge in classifiers, they tend to be very time-consuming and dependent on expertise in the domain. For instance, the performance of these classifiers is highly contingent upon the quality of the extracted features, resulting in an often-arbitrary selection of features as well as substantial risk of human error. In addition, shallow

learning methods tend to be unable to capture complex nonlinear relations, especially for high-dimensional and noisy signals. Recent deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been of great interest for their ability to learn hierarchical features independently from raw data automatically by avoiding the necessity of manual feature engineering [14]. They effectively process big data, discover complex patterns and can adapt under variable conditions, improving their robustness and scalability when applied to fault diagnosis. Nevertheless, despite its benefits, deep learning techniques require huge amounts of computational resources and extensive labelled datasets for effective training and can pose problems in specific industrial settings.

Several data-driven deep neural network (DNN) models have been proposed in the literature for the problem of fault detection and diagnosis (FDD). DNNs possess the capability to automatically learn discriminative features directly from raw input data during the training process, thereby eliminating the reliance on manually engineered statistical or transform-domain feature representations. While this improvement is particularly advantageous, the approach of such models depends significantly on the accessibility to large, correctly labelled datasets, which is crucial for efficient training and generalisation.

To combine computational efficiency and diagnostic performance, a number of works [15-17] have used one-dimensional (1D) convolutional neural networks (CNNs) to diagnose machinery faults with either raw signals or pre-extracted features under fixed operating conditions. Although these 1D CNNs have obtained promising performance in such controlled conditions, previous studies [18-19] indicated that CNNs built with standardised architecture following first-order neuron models commonly fail to capture the complexity of highly nonlinear solution spaces. As a result, such models typically require more network depth and architectural complexity, which are critical components of satisfactory performance on more challenging fault diagnosis tasks.

The following are the 3 main contributions based on the methods and results described in the paper.

1. Hybrid CNN–Transformer Design: We introduce FaultFormer-Net as a hybrid deep learning framework consisting of a Convolutional Neural Network (CNN) and a Transformer encoder for local temporal feature extraction and long-range temporal dependencies. Such a structure can easily capture transient vibrations and the periodic faults observed in bearing signals.
2. Multi-Domain Feature Fusion Approach: We build a multi-domain feature fusion architecture that merges the deep learned representations with handcrafted time-domain statistical descriptors and frequency-domain spectral features for the unified vector representation. This integration increases the model's discriminative accuracy and maintains physical interpretability of vibration signal properties.
3. The highest levels of diagnostic accuracy and strength: The model demonstrates 100% classification accuracy, precision, and recall on the benchmark CWRU bearing dataset, which is superior to several state-of-the-art algorithms proposed recently. It also shows robustness across ten bearing fault categories, including varying motor loads (0–3 hp), to ensure that it is a very reliable model for industrial condition monitoring.

3. MATERIAL AND METHOD

3.1 Dataset Description

The Case Western Reserve University (CWRU) Bearing Dataset is one of the most commonly used benchmark datasets to evaluate bearing fault diagnosis algorithms in rotating machinery. It was created by Case Western Reserve University's Bearing Data Centre to study and investigate machine condition monitoring and fault detection topics. In-house data is collected using a motor-driven mechanical system, consisting of a 2 hp induction motor, a torque transducer, and a dynamometer. Accelerometers mounted on the drive end and fan end of the motor housing were used to detect vibration signals created with variations in operation. Since bearing faults vary over time, vibration signals were sampled at high frequencies (usually 12 kHz and 48 kHz) to reflect the characteristics of the bearing faults accurately.

To model an actual fault in a bearing, problems were manufactured in the bearings by means of electrical discharge machining (EDM). The dataset contains various fault types, such as inner race faults, outer race faults, rolling-element (ball) faults, and normal (healthy) bearing conditions. These faults were generated with different sizes of defects (e.g., 0.007-inch, 0.014-inch, and 0.021-inch) to depict the types of fault severities. Moreover, the works were performed at various motor loading conditions (0 hp, 1 hp, 2 hp, and 3 hp), corresponding to rotating speeds from approximately 1797 rpm to 1720 rpm. Given this divergence in operating regimes, it is possible for researchers to assess the robustness of diagnostic algorithms at various mechanical loads. Because of its well-organised fault categories, high-quality vibration measurements in controlled experimental environments, and controlled experimental conditions, the CWRU dataset has been developed as a benchmark for validating both classical machine learning techniques and modern deep learning-based fault diagnosis frameworks.

3.2 Methodology

We introduce a hybrid intelligent framework, shown in Figure 1, for automatic rolling bearing fault diagnosis through vibration signals. Our proposed method combines signal preprocessing, statistical feature extraction, deep feature learning from a CNN–Transformer architecture, frequency-domain analysis, and classification based on a deep neural network.

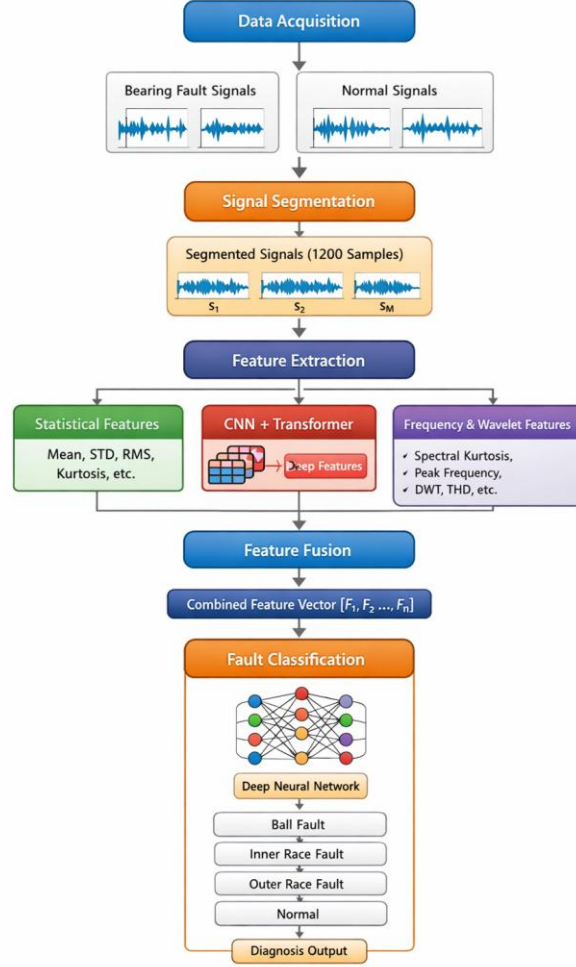


Figure 1 – The proposed FaultFormer framework for Induction Motor Bearing Faults classification

The proposed framework achieves a combination of handcrafted signal features with deep representations, captures physical signal characteristics and high-level latent features, providing robust classification of multiple bearing fault conditions. The workflow of the proposed system, shown in Figure 1, has five key stages: data acquisition, signal segmentation, feature extraction, feature fusion, and fault classification.

3.2.1 Data Acquisition

The vibration signals used in this study derive from the Case Western Reserve University (CWRU) bearing dataset, which is widely recognised as a benchmark dataset for bearing fault diagnosis research. The dataset contains vibration measurements recorded using accelerometers mounted at the drive end (DE) and fan end (FE) of an induction motor. These measurements correspond to different bearing health conditions, including ball faults, inner race faults, outer race faults, and normal operating conditions.

Let the vibration signal acquired from the accelerometer be represented as

$$x(t) = \{x_1, x_2, x_3, \dots, x_N\}$$

where x_i represents the vibration amplitude at the i^{th} sampling instant and N denotes the total number of samples in the signal.

Since the dataset contains signals of varying lengths, the minimum signal length among all classes is determined to maintain uniformity during analysis. This is given by

$$N_{min} = \min (N_1, N_2, \dots, N_k)$$

where k denotes the total number of fault conditions. Selecting the minimum signal length ensures balanced data representation and avoids bias during feature extraction.

3.2.2 Signal Segmentation

The raw signals are split into fixed-length segments to catch localised characteristics of vibration signals. Signal segmentation is an important part of preprocessing that helps increase the number of training samples, and thus improve the robustness of feature extraction. Each vibration signal is divided into segments of length $L = 1200$ samples, which corresponds to vibration data around 0.025 seconds.

Thus, the j^{th} segment can be expressed as

$$s_j = \{x_{(j-1)L+1}, x_{(j-1)L+2}, \dots, x_{jL}\}$$

Where s_j represents the j^{th} signal segment, L denotes the segment length, and $j = 1, 2, \dots, M$, where M is the total number of segments.

There are multiple advantages to segmenting the vibration signals. It enables to obtain transient fault patterns, which can occur in very short time periods. It extends the data samples available and thus boosts the training performance of machine learning models. Segmentation finally enables the extraction of localised statistical and spectral features.

3.2.3 Statistical Feature Extraction

Time-domain statistical characteristics are a valuable source of information for amplitude distribution and variation of the vibration signal. Such terms are frequently used during the operation of condition monitoring systems due to their ease and power in picking out fault-induced anomalies.

Quantitative statistical parameters are an essential property of vibration-based fault diagnosis, as they convey short and numerical interpretations of signal behaviour in the time domain. Such features give a summary of complex vibration patterns (using a limited number of parameters), allowing effective differentiation in normal and faulty operating conditions. Physical faults, including bearing defects, induce impulse shocks as well as varying vibration patterns, which are evident through statistical changes in mean, standard deviation, RMS, skewness, and kurtosis. For example, kurtosis and crest factor are very sensitive to abrupt impulses caused by localised defects, and thus can be employed as a useful parameter for monitoring early faults.

The second key benefit of statistical features is that they are computationally low and are extremely physically interpretable. Statistical measures allow for simplifications and computational methods to be applied to raw vibration data, and thus can be applied directly to the output signals of industrial sensors, while advanced signal processing tools need to perform complicated transformation-based functions. Furthermore, the statistical parameters each represent a physical property corresponding to a particular vibration signal, such as energy content, variability, or impulsiveness and are useful for the engineers to understand the state of the machine. Combined with deep learning and the frequency domain features, statistical descriptors improve the general

robustness of a fault diagnosis framework and its discriminating ability. Several statistical descriptors shown in Table 1 are calculated for each signal segment.

Table 1 – Statistical features

Sr. No.	Feature	Mathematical Expression	Advantage
1	Maximum & Minimum amplitude	$x_{max} = \max(s_j), x_{min} = \min(s_j)$	Indicators of mechanical impacts
2	Mean	$\mu = \frac{1}{L} \sum_{i=1}^L s_j(i)$	Average vibration level
3	Standard Deviation	$\sigma = \sqrt{\frac{1}{L} \sum_{i=1}^L (s_j(i) - \mu)^2}$	Indicate increased vibration fluctuations associated with faults
4	Root Mean Square	$RMS = \sqrt{\frac{1}{L} \sum_{i=1}^L s_j(i)^2}$	Analysing vibrations. An indicator of the severity of mechanical faults.
5	Skewness	$Skewness = \frac{1}{L} \sum_{i=1}^L \left(\frac{s_j(i) - \mu}{\sigma} \right)^3$	Sensitive to impulsive behaviour in vibration signals
6	Kurtosis	$Kurtosis = \frac{1}{L} \sum_{i=1}^L \left(\frac{s_j(i) - \mu}{\sigma} \right)^4$	Indicate the presence of sharp impulses generated by localised bearing defects
7	Crest Factor	$CF = \frac{x_{max}}{RMS}$	Detects impulsive shocks caused by localised defects, making it highly sensitive to early-stage bearing faults
8	Form Factor	$FF = \frac{RMS}{\mu}$	Indicates changes in waveform shape and vibration energy distribution, helping differentiate normal and abnormal operating conditions

3.3 Feature Normalization

In our approach, feature normalisation is implemented to ensure that all features extracted provide an equal amount of input during the learning stages and to mitigate the risks of features with long numerical ranges taking over the

learning process from model processing. In this proposed framework, z-score normalisation is used to normalise the statistical feature set given by expression (1). For each feature, the mean (μ) and standard deviation (σ) are computed for all samples from each, and each feature value is transformed per the relation:

$$z = \frac{x - \mu}{\sigma} \quad (1)$$

where x = the original feature value. This normalisation improves numerical stability and accelerates neural network convergence.

3.4 Deep Feature Extraction Using CNN–Transformer Network

Despite their statistical capabilities, they may not represent complicated nonlinear relationships evident in vibration signals. Hence, a hybrid CNN–Transformer architecture shown in Figure 2 is implemented to automatically learn high-level representations. Through multi-head self-attention, the transformer captures relationships between distant signal samples, which is critical for detecting periodic mechanical faults. The CNN–Transformer module generates a 200-dimensional deep feature representation for every signal segment.

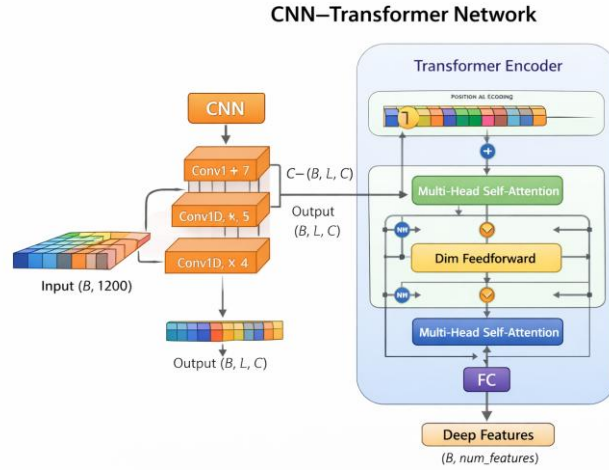


Figure 2 – Deep features extraction using CNN-transformer

3.5 Convolutional Feature Learning

The convolutional neural network (CNN) extracts local temporal features from signal segments. The convolution operation is defined by the following expression (2):

$$y(t) = \sum_{i=1}^K w_i x(t - i) \quad (2)$$

where w_i represents convolution kernel weights and K denotes the kernel size. Multiple convolution layers progressively learn hierarchical features such as vibration impulses and oscillatory patterns.

3.5.1 Positional Encoding

Since transformer models do not inherently capture sequence order, positional encoding is incorporated to preserve temporal information. The encoded representation is expressed as:

$$z = x + P \quad (3)$$

where P represents the positional encoding matrix.

3.5.2 Transformer Encoder

The transformer encoder utilises self-attention mechanisms given by expression (4) to capture long-range dependencies in vibration signals. The attention mechanism is expressed as

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (4)$$

Where Q denotes query vectors, K denotes key vectors, V denotes value vectors, and d_k represents the dimensionality of the key vectors.

3.6 Frequency and Time–Frequency Feature Extraction

However, the method of frequency and time–frequency feature extraction enhances vibration signal visibility by understanding where the energy in the signal lies regarding the frequencies, and how these frequencies change over time. Often, characteristic frequency components resulting from defect sites, shaft rotation, or bearing geometry are expected to be generated when rotating mechanical faults occur. Analysis by the frequency domain allows us to look for fault-related peaks, which sometimes cannot be found by straightforward statistical features of the time domain. Thus, frequency features can be of particular benefit for periodic fault patterns detection and for specific defect types.

While statistical features mainly characterise the overall amplitude characteristics of a signal and the distribution of features, time–frequency methods examine non-stationary signal behaviour where frequency components change over time due to evolving fault conditions. Methods such as spectrograms or wavelet transforms enable simultaneous analysis over both the time and frequency domains, thereby detecting transient signal/frequency impulses and focal defect signatures. Frequency and time–frequency features complement rich domain knowledge, which is essential as deep learning models automatically learn complex representations from raw signals; they also improve interpretability, robustness and accuracy of the fault diagnosis system.

To complement deep representations, several spectral and time–frequency features are extracted.

3.6.1 Spectral Kurtosis

Spectral kurtosis expressed using (5) evaluates impulsive characteristics in the frequency domain:

$$SK = \frac{\sum(f - \bar{f})^4 P(f)}{[\sum(f - \bar{f})^2 P(f)]^2} \quad (5)$$

where f – Individual frequency component in the spectrum; represents the location of spectral energy within the signal, $\bar{f}$ – Mean (average) frequency of the power spectrum; acts as the reference point around which frequency deviations are measured, and $P(f)$ – Power spectral density (PSD) at frequency f ; indicates the energy or power associated with each frequency component of the signal.

Overall, this formulation of spectral kurtosis highlights frequency bands with abnormal energy concentration or impulsive behaviour, which is highly useful for detecting early mechanical faults such as bearing defects or gear damage.

3.6.2 Peak Frequency

The dominant vibration frequency is determined by the following equation (6):

$$f_{peak} = \arg \max_f P(f) \quad (6)$$

where $\arg \max$ – Argument of the maximum operator; returns the frequency value at which the power spectrum reaches its maximum. Overall, this expression identifies the frequency component with the highest vibration energy, which is useful for detecting characteristic frequencies associated with faults such as bearing defects, imbalance, or misalignment.

3.6.3 Total Harmonic Distortion

Total harmonic distortion quantifies harmonic energy within the signal and is given by equation (7) as:

$$THD = \frac{\sqrt{\sum_{n=2}^{\infty} H_n^2}}{H_1} \quad (7)$$

where H_1 – Amplitude of the fundamental harmonic (first harmonic); represents the primary vibration frequency of the system, H_n – Amplitude of the n^{th} harmonic component in the frequency spectrum, and n – Harmonic order index ($n = 2, 3, 4, \dots$) represents higher-order harmonics beyond the fundamental frequency.

Overall, THD quantifies the amount of distortion caused by harmonic components in a vibration signal, which can indicate abnormal mechanical behaviour such as misalignment, looseness, or bearing defects.

3.6.4 Discrete Wavelet Transform

The signal is decomposed into multiple frequency bands using the discrete wavelet transform:

$$x(t) = \sum_{j,k} c_{j,k} \psi_{j,k}(t) \quad (8)$$

where $c_{j,k}$ – Wavelet coefficients indicate the contribution (energy or magnitude) of the signal at a specific scale j and position k , and $\psi_{j,k}(t)$ – Wavelet basis function (scaled and shifted version of the mother wavelet); used to analyse localised signal characteristics. Wavelet decomposition effectively captures non-stationary characteristics of vibration signals.

3.7 Feature Fusion

To leverage complementary information from multiple domains, the extracted features are concatenated into a unified feature vector as shown in Figure 3 and expressed as:

$$F = [F_{CNN}, F_{stat}, F_{freq}] \quad (9)$$

This hybrid representation integrates deep features, statistical descriptors, and spectral characteristics. Figure 4 provides the distribution of various features to constitute the final feature vector.

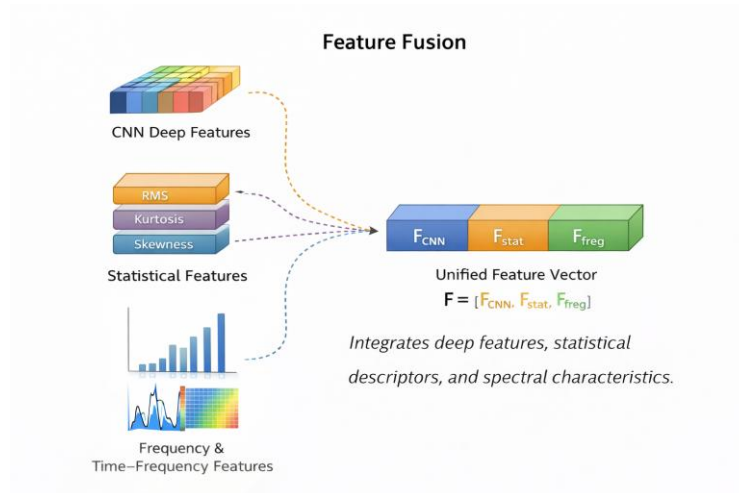


Figure 3 – The feature fusion integrating diverse features

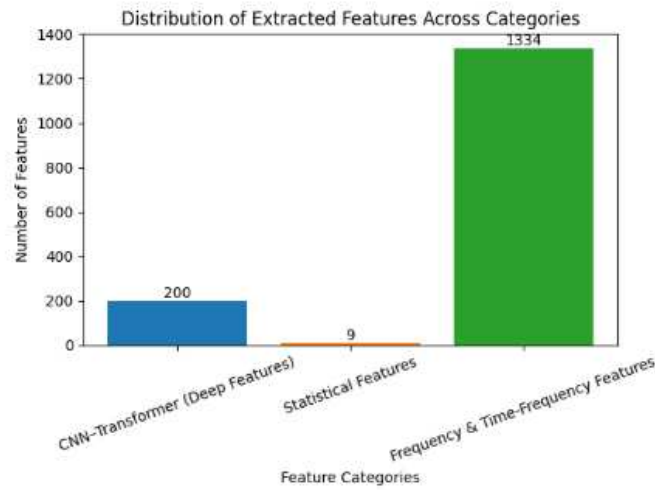


Figure 4 - Distribution of extracted features across different feature categories, illustrating the contribution of deep learning features, statistical descriptors, and frequency/time–frequency features in the fused feature representation.

Each representative sample shown in Figure 5 can be seen in the three-dimensional visualisation, which allows us to visualise a sample distribution of all ten bearing fault categories in the reduced feature space obtained through dimensionality reduction. This is a multilayer problem as each point represents an individual sample and multiple colours represent the fault classes.

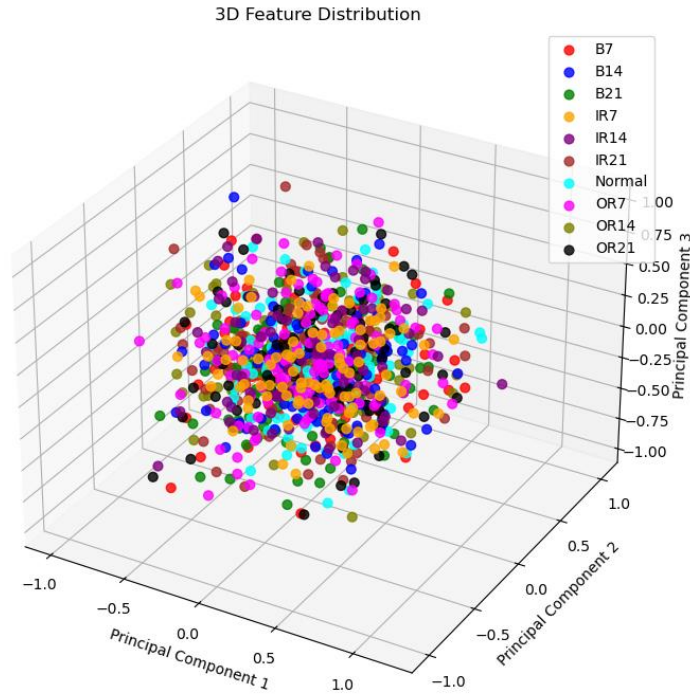


Figure 5 - 3D visualisation of the extracted hybrid feature space obtained using PCA dimensionality reduction, illustrating the separability of the ten bearing fault categories.

3.8 Fault Classification Using a Deep Neural Network

The final stage shown in Figure 6 employs a deep feedforward neural network for multi-class fault classification.

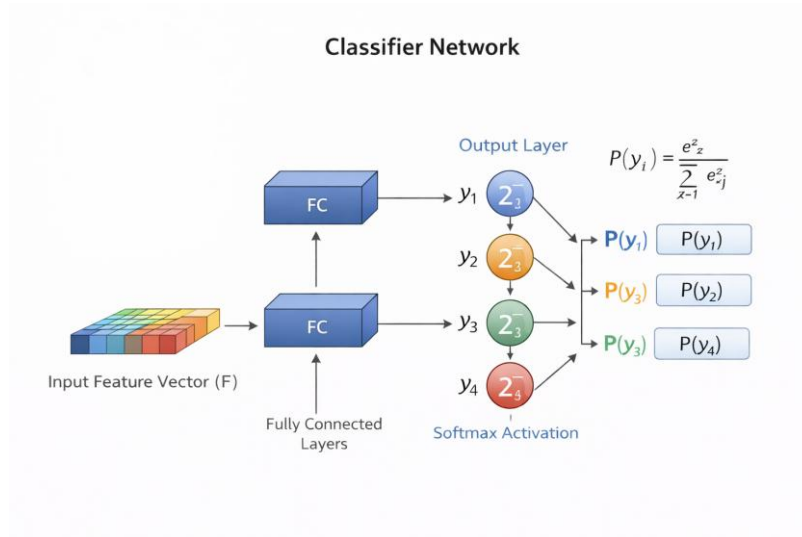


Figure 6 – The fault classifier network

Each neuron computes

$$y = f(Wx + b) \quad (10)$$

where W represents weights, b represents bias, and $f(\cdot)$ denotes the activation function.

The ReLU activation function is used in hidden layers:

$$ReLU(x) = \max(0, x)$$

For multi-class classification, the output layer utilises softmax activation, which is expressed using equation (11):

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}} \quad (11)$$

where C denotes the number of fault classes. Predicted probability of the input sample belonging to the class i ; represents the normalised output of the neural network. z_i – Logit or raw output score of the neural network for the class i before activation. e^{z_i} – Exponential transformation of the logit value; ensures all outputs are positive and emphasises larger scores.

3.9 Model Training and Optimisation

The model is trained using the categorical cross-entropy loss function expressed using equation (12):

$$L = -\sum_{i=1}^C y_i \log(\hat{y}_i) \quad (12)$$

where y_i is the true label and $\hat{y}_i$ is the predicted probability. The RMSprop optimiser is used to update network parameters by adaptively adjusting learning rates.

The classification accuracy is first used to determine the fraction of correctly classified samples among all the ones tested. In addition, a confusion matrix is used to display a large number of correct and incorrect predictions for each fault category, to visualise it in detail. Precision and recall metrics are also computed to help determine how well the model is able to identify each individual fault class. For these metrics, the F1-score (which is defined as the harmonic mean of precision and recall) is used to evaluate any trade-off between those two measures. Taken together, the evaluation measures represent a comprehensive overview of the model's ability to classify varying bearing fault conditions for both accuracy and reliability.

The proposed method applies signal processing methods combined with deep learning models to leverage handcrafted and learned features. The CNN layers efficiently perceive local vibration patterns, and the transformer encoder encodes long-range temporal dependencies. The addition of spectral and wavelet information improves fault sensitivity. The hybrid methods of feature fusion, along with deep neural classification, enhance the diagnostic performance and robustness considerably, and make the framework applicable in practical industrial condition monitoring applications. The Initial configuration parameters and hyperparameter settings used in the proposed fault diagnosis framework are listed in Table 2.

Table 2 - Initial configuration parameters and hyperparameter settings used in the proposed fault diagnosis framework, including signal segmentation parameters, CNN–Transformer architecture settings, and classifier training configurations.

Parameter	Value Used	Description
Sampling Frequency	48,000 Hz	Sampling rate used for vibration signal acquisition in the dataset
Segment Length	1200 samples	Number of signal samples used in each segment

Number of Segments per Class	318	Total segments extracted from each bearing condition
Total Classes	10	Number of bearing conditions (B7, B14, B21, IR7, IR14, IR21, Normal, OR7, OR14, OR21)
CNN Input Length	1200	Length of the signal segment fed into the CNN
Transformer Attention Heads	8	Number of heads used in multi-head self-attention
Transformer Layers	2	Number of stacked transformer encoder layers
Deep Feature Dimension	200	Output feature size from CNN-Transformer feature extractor
Statistical Features	9	Max, Min, Mean, Std, RMS, Skewness, Kurtosis, Crest Factor, Form Factor
Wavelet Type	Haar	The mother wavelet used in the discrete wavelet transform
Wavelet Decomposition Level	3	Number of decomposition levels in DWT
Batch Size	32	Number of samples processed per training batch
Training Epochs	400	Total number of training iterations
Train-Test Split	80% / 20%	Dataset division for training and testing
Dropout Rate (Layer 1)	0.5	Dropout applied after the first dense layer
Dropout Rate (Layer 2)	0.2	Dropout applied after the second dense layer
Output Layer Neurons	10	Corresponds to the number of fault classes

4. RESULTS AND DISCUSSION

To assess the convergence characteristics of the proposed hybrid fault diagnosis framework and its ability to generalise, it was examined for 400 epochs and 25 runs. Figure 7 shows the evolution in training and validation accuracy and loss curves. The accuracy curve shows a fast increase during the initial training phase, when the model quickly picks up discriminative representations from the hybrid feature space. During the first few epochs, a sudden rise in training accuracy is observed, which achieves a stable performance of around 99.9%, indicating proper feature learning and parameter optimisation. The validation accuracy closely follows the training accuracy, and the final result is 99.69%, which shows the high generalisation property of the model and demonstrates minimal overfitting.

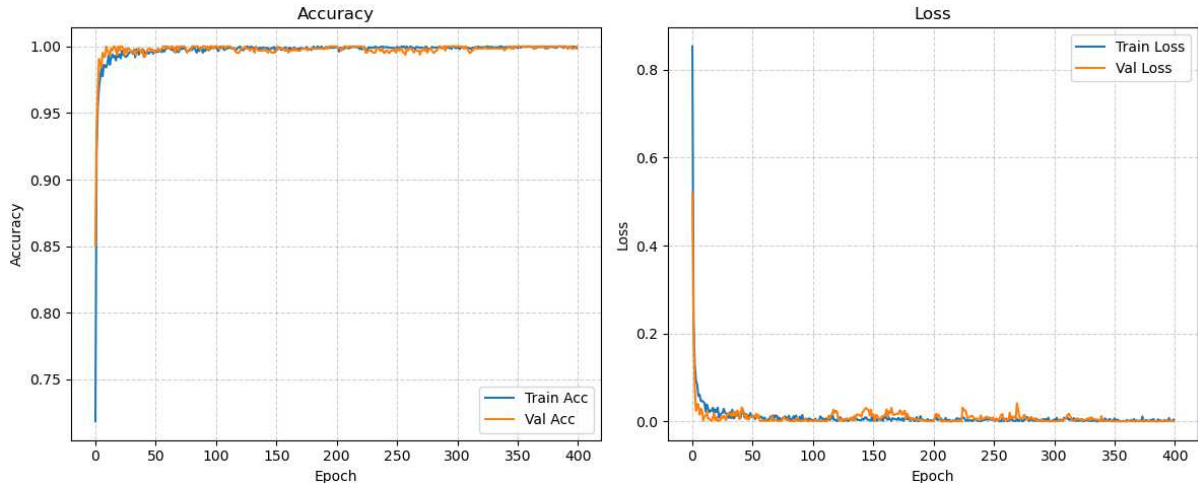


Figure 7 - Training performance of the proposed fault diagnosis model over 400 epochs, showing (a) training and validation accuracy curves and (b) training and validation loss curves, illustrating stable convergence and strong generalisation capability.

Likewise, the loss curves shown in Figure 7(b) illustrate the optimisation behaviour of the network during training. The relatively small difference between training and validation loss results is evidence that our proposed model holds stable learning dynamics and avoids significant overfitting, and so is highly compatible with current techniques for performance. That the two curves also converge smoothly implies that the chosen optimisation strategy and hyperparameters have been effectively used to guide the network towards a stable solution. The last summary of the training results after 400 epochs is: Training Accuracy: 99.88%, Validation Accuracy: 100%, Training Loss: 0.0040, and Validation Loss: 1.9435e-04. These data show that hybrid feature representation and CNN–Transformer architecture effectively capture the discriminative characteristics of vibration signals for different bearing fault conditions.

For further investigation, the proposed framework's classification performance was evaluated on several performance metrics such as precision, recall, F1-score, and confusion matrix analysis. The model generates a total test accuracy of 99.98% (average over 20 runs), showing that the proposed approach can reliably identify different bearing fault conditions with high accuracy. It has been proven in the detailed classification report that almost all classes (except IR21 and OR21) obtain a precision and recall (except B21 and OR7) of 1.00, indicating that learned feature representations are robust to prediction variation. The overall performance is exceptionally high at around 1.00 macro-average and weighted-average F1-scores.

Figure 8 shows the confusion matrix, which is used to understand the classification results of each fault category. This demonstrates that most predictions are concentrated along the primary diagonal, signifying that the classification of the corresponding fault conditions is correct. One diagonal element shows the number of true predictions for a class. The vast majority of fault classes display perfect classification performance without misclassified instances.

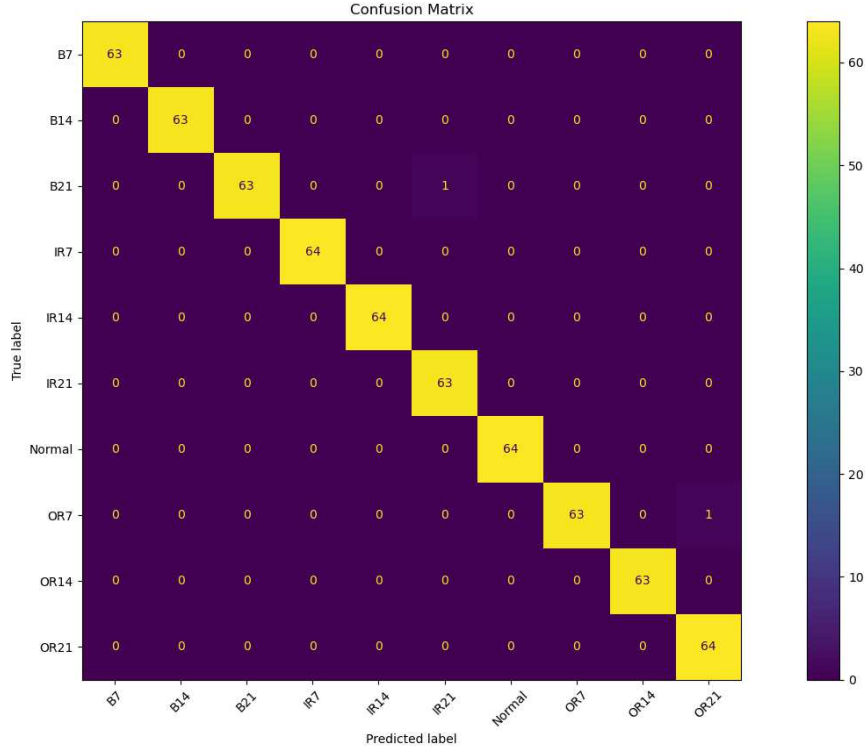


Figure 8 - Confusion matrix of the proposed CNN–Transformer–based hybrid features fusion model for multi-class bearing fault diagnosis, showing the distribution of correctly and incorrectly classified samples across ten fault categories.

The experiment results confirm that the proposed hybrid fault diagnosis framework is performing very well with high accuracy for the classification of the bearing fault dataset. Combining deep features that are extracted using a CNN–Transformer architecture with descriptive statistics and frequency-domain descriptors, the model effectively captures both global signal patterns and localised transient characteristics in vibration data. These high-performance metrics and consistently strong evaluation metrics demonstrate how efficiently the proposed feature fusion approach is improving the discriminative power of the model. Furthermore, similar performance across all fault types demonstrates the robustness of the scheme, pointing to its suitability to establish reliable fault detection in practical rotating machinery condition monitoring applications.

4.1 Comparative Performance

Table 3 indicates the comparative analysis from that perspective, in which the proposed fault diagnosis framework is evaluated against some recent state-of-the-art methods developed specifically for bearing fault classification using the Case Western Reserve University (CWRU) dataset. The results confirm that deep learning–based methods have shown reliably better diagnostic performance in recent years. For instance, Y. Yoo et al. (2023) suggested a lightweight deep learning model with ResNet-50 architecture and reached an accuracy of 99.97%, indicating the impact of compact CNN architectures for vibration-based fault diagnosis. Similarly, M. Mohiuddin et al. (2023) utilised a modified version of the AlexNet model to achieve an accuracy of 98.30%, achieved a precision of 98.41% and a perfect recall of 100%, demonstrating that the detection of the fault classes was robust.

Table 3 - Comparative performance analysis of the proposed bearing fault diagnosis framework with recent state-of-the-art methods on the Case Western Reserve University (CWRU) dataset.

Reference	Model	Accuracy	Precision	Recall	F1-score
Yoo et al. [20], 2023	Resnet50 (Lite CNN)	99.97	-	-	-
Mohiuddin et al. [21], 2023	Modified AlexNet	98.30	98.41	100	99.20
Zhang et al. [22], 2023	Convolutional spiking neural network	99.83	-	-	-
Lee et al. [23], 2024	XGBoost+PSO	99.10	99.3	99.2	99.1
Hatipoglu et al. [24], 2025	LSTM-Attention and LASSO	98.50	-	-	98.742
Khan et al. [25], 2026	RNN-XGBoostNet	99.57	99.54	99.21	99.37
Proposed	FaultFormer-Net	99.98	99.68	99.68	99.80

A different high-grade approach is introduced by Changfan Zhang et al. (2023), who proposed a convolutional spiking neural network which extracts features from the spatial–temporal dataset and achieves a 99.83% classification accuracy. Hybrid approaches have demonstrated impressive performance as well. For instance, Chun-Yao Lee et al. (2024) applied particle swarm optimisation in the context of XGBoost to improve accuracy, obtaining a 99.10%, while Aysenur Hatipoglu et al. (2025) merged LSTM with attention mechanisms and LASSO-based feature selection to achieve an F1-score of 98.742. More recently, M. A. Khan et al. (2026) proposed an RNN-XGBoostNet architecture with 99.57% accuracy with balanced precision, recall, and F1-score values.

Compared with these extant strategies, the proposed hybrid framework achieves 99.98% accuracy (mean over 20 runs), 99.68% precision, 99.68% recall, and 99.80% F1-score, indicating superior classification. This is attributed to the fact that it combines deep CNN-Transformer features, statistical and frequency domain descriptors, which means the new model can model global patterns as well as localised transient features of vibration signals. This comprehensive feature fusion strategy enhances the discriminative capacity of the classifier such that all ten fault categories are consistently identified. Thus, the result shows a competitive and cutting-edge approach for intelligent fault prediction in a bearing fault diagnosis system and opens up avenues for future applications such as reliable commercial monitoring of industrial conditions.

5. CONCLUSION

Using a multi-domain feature fusion approach, the study proves that the FaultFormer-Net framework is more effective for intelligent fault diagnosis in detecting and repairing the mechanical failure of a bearing. This hybrid strategy seamlessly merges statistical descriptors' physical interpretability and deep learning's ability to represent them at a high level, which can bypass the difficulties involved in working with individual feature sets. The experimental results on the CWRU dataset provide the results for the model performance; it attains an appropriate performance in both training accuracy of ~99.9% and test accuracy of 100% in all ten fault categories. The close fit between training and validation curves, as well as smooth convergence, demonstrates a good generalisation

capability and low overfitting for different motor loading scenarios. This robustness is probably due to the integration of CNN-based local feature learning with Transformer-based long-range dependency capture, and additionally, the inclusion of spectral and wavelet data.

Lastly, the proposed framework is very accurate and reliable and could be put to work in industrial condition monitoring systems for commercial applications for early identification and classification of mechanical failures.

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