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Edge-computing enabled dual-branch joint decision framework for PMSLM air-gap nonuniformity fault diagnosis



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Highlights:

- Dual-branch diagnosis combines 1-D signals and 2-D Hankel images.
- Lightweight multiscale blocks and ELA enhance fault-sensitive features.
- Edge deployment supports practical fault monitoring.

Abstract: Owing to its precise positioning capability and fast dynamic behavior, the permanent magnet synchronous linear motor (PMSLM) has found broad application in advanced manufacturing and related industrial systems. However, air-gap nonuniformity faults, which are typical faults in PMSLMs, can cause thrust fluctuations and other adverse effects, thereby impairing stable equipment operation and potentially leading to safety accidents. Therefore, accurate diagnosis of these faults is essential. To address this issue, a dual-branch multiscale diagnostic method based on complementary feature utilization and joint decision-making is proposed. First, a 1-D diagnostic branch is developed to extract discriminative features from subtle fault-induced variations in the external magnetic field signal. Meanwhile, a Hankel-matrix mapping converts each 1-D external magnetic field signal into a grayscale image, which is subsequently processed by a dedicated 2-D branch to capture spatial structures and multiscale texture patterns. Finally, a joint decision layer is designed to comprehensively exploit the outputs of the two branches for fault identification. Simulation results show that the proposed method achieves a fault diagnosis accuracy of 99.83% under noise-free conditions and maintains an accuracy of 93.53% under white Gaussian noise at an SNR of 20 dB. Experiments using measured data collected from the developed PMSLM experimental platform, together with deployment experiments on edge computing platforms, further verify the effectiveness of the proposed model.

Keywords: permanent magnet synchronous linear motor (PMSLM); Hankel matrix; dual-branch; air-gap nonuniformity fault; fault diagnosis



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1. Introduction

Linear motors feature simple structures, high acceleration, and ease of control [1–4], and can be used to drive industrial equipment such as linear compressors [5,6]. In particular, the permanent magnet synchronous linear motor (PMSLM) is characterized by high thrust density and efficiency, rapid dynamic response, accurate motion control, and reliable operation. At present, PMSLMs have been widely applied in high-precision manufacturing, rail transit, linear drive platforms, and automation equipment [7–9]. For a double-stator PMSLM, its parameters may vary during operation due to working conditions and environmental factors. For example, assembly deviations between the stator and mover [10], insufficient straightness of the guide rail, and other factors may cause air-gap nonuniformity fault in PMSLM [11]. This fault and subsequent eccentric faults can cause electromagnetic thrust fluctuations, abnormal vibration, and noise. These disturbances can reduce output accuracy and efficiency, accelerate component wear, shorten motor service life, and even threaten operational safety. Therefore, research on the diagnosis of air-gap nonuniformity faults in PMSLMs is of great engineering significance [12].

In fault signal representation and intelligent classification, motor fault diagnosis still faces major challenges. Signal processing is a key step. It directly affects how clearly fault features can be distinguished. Many studies use methods such as wavelet transform (WT) and empirical mode decomposition (EMD) to decompose raw signals and extract frequency-domain, time-frequency, or multiscale features. For example, in [13], discrete WT was employed to extract multiscale energy features from the stator current under predictive torque control. These features were used to diagnose broken rotor bar faults and assess their severity in induction motors. In [14], a Kalman-filter-based EMD method was combined with a lightweight multilayer perceptron to enable motor fault diagnosis on edge devices. However, these methods usually rely on expert experience to choose feature transformation strategies. Their ability to adaptively represent weak fault disturbances is still limited in complex noisy environments.

Deep learning has become widely used in motor fault diagnosis in recent years. Models such as convolutional neural networks (CNNs), recurrent neural networks, Transformers, and their improved variants are used to learn features [15,16]. Guan *et al.* [17] combined time-shifting and wavelet-based denoising with a 1-D CausalConvNet to identify induction-motor bearing faults from motor current signals. Hou *et al.* [18] proposed a lightweight model, which integrated learnable comb-filter kernels into a 1-D CNN to extract weak fault features from motor current signals under limited training-sample conditions. Xu *et al.* [19] proposed an asynchronous motor fault diagnosis method based on an optimized deep bidirectional long short-term memory network. Yang *et al.* [20] employed AlexNet to classify 2-D images generated from three-phase current time-series signals through Gramian angular field encoding, thereby enabling the assessment of different permanent magnet demagnetization levels in a linear motor feed system. Xu *et al.* [21] reconstructed fault features by applying difference and envelope processing to air-gap magnetic flux density signals and employed a Bayesian-optimization-based CNN to identify stator winding position faults in a modular moving-magnet-type permanent magnet synchronous linear motor. To address the problem of insufficient fault samples in motor bearing fault diagnosis, Fu *et al.* [22] proposed a Transformer-based auxiliary classifier generative adversarial network. Digital twin (DT) technology is also increasingly combined with data-driven learning to address the shortage of fault or degradation data and improve intelligent condition monitoring. Wang *et al.* [23] combined a simplified electrochemical model with incremental learning to build a lithium-battery DT model. This model

supports online updates throughout the battery life cycle. DT-assisted learning has also been studied for bearing remaining useful life prediction [24]. For gearbox fault diagnosis, DT-generated data were combined with deep transfer learning to bridge the gap between simulated and real operating conditions [25]. Despite these advances, existing intelligent fault diagnosis methods still rely mainly on a single representation of monitoring signals. These methods do not jointly use 1-D waveform information and 2-D spatial information. This may limit their ability to distinguish similar fault classes under noisy conditions. Some deep diagnostic models also have many parameters and high computational costs. These requirements make them difficult to deploy on edge devices with limited resources.

To address these limitations, this study proposes a lightweight dual-branch joint decision network (LD-JDNet) for air-gap nonuniformity fault diagnosis in PMSLM. Different from the methods that use only 1-D signals or 2-D images, LD-JDNet uses both waveform variations and Hankel-image spatial textures. Both types of information are obtained from the same external magnetic field signal. The main contributions are as follows:

(1) A dual-representation diagnostic framework is developed. It uses original 1-D external magnetic field signals and their corresponding 2-D Hankel grayscale images. The two branches analyze fault-induced waveform variations and spatial texture patterns in complementary ways. This improves the discrimination of similar fault categories under noisy conditions.

(2) The efficient location attention (ELA) mechanism is introduced into the 2-D branch. It is used to enhance fault-sensitive regions in Hankel images. ELA encodes spatial information along two orthogonal directions to emphasize salient texture structures and suppress irrelevant responses. This improves feature extraction capability and robustness under noise interference while adding limited computational overhead.

(3) Lightweight multiscale feature extraction structures are designed for each diagnostic branch. These structures reduce the parameter count and computational cost while maintaining high diagnostic accuracy. Deployment experiments also show that the framework is feasible for fault diagnosis on platforms with limited resources.

The rest of this study is organized as follows. Section 2 describes the finite-element modeling of the PMSLM. It also covers the acquisition of air-gap nonuniformity fault signals. Section 3 explains the construction of Hankel grayscale images and details the architecture of LD-JDNet. Section 4 reports the simulation setup and analyzes the classification performance, noise robustness, and computational efficiency of the proposed method. Section 5 presents the prototype experiments and edge-device deployment validation. Finally, Section 6 concludes this study.

2. Finite element analysis of PMSLM and fault signal acquisition

The 3-D topology of the PMSLM is shown in Figure 1a. The structure mainly consists of two parts: the mover and the double-sided stator. The stator is composed of upper and lower back irons and alternately arranged N- and S-pole permanent magnets facing each other, while the mover is the moving component of the PMSLM and mainly consists of an epoxy-resin coil structure. The main structural parameters of the PMSLM are listed in Table 1.

The air-gap nonuniformity faults of the PMSLM can be classified into four types: right-dynamic air-gap nonuniformity fault, left-dynamic air-gap nonuniformity fault, up-static air-gap nonuniformity

fault, and down-static air-gap nonuniformity fault. These four types of air-gap nonuniformity faults are shown in Figure 1b.

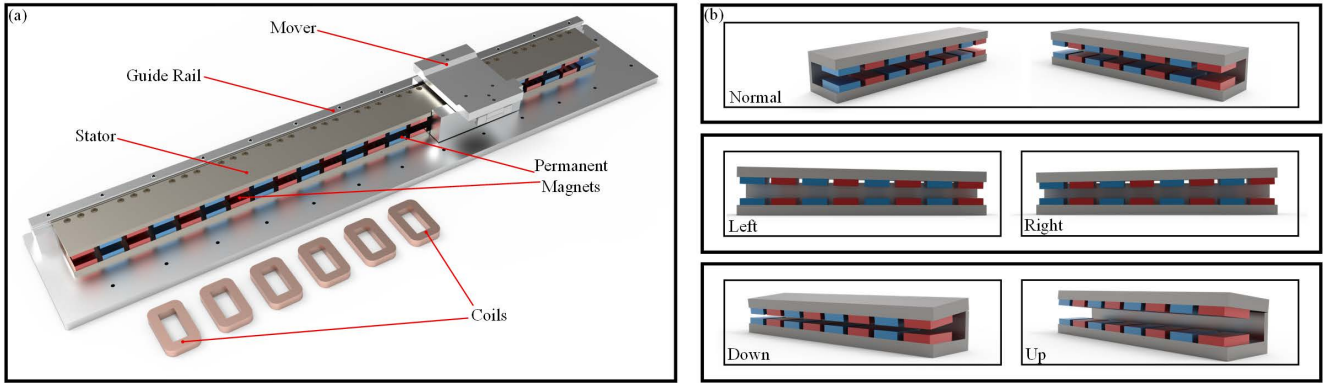


Figure 1. PMSLM structure and air-gap nonuniformity faults. (a) 3-D structure of the PMSLM; (b) Schematic diagram of air-gap nonuniformity fault.

Table 1. Main structural parameters of the PMSLM.

Parameter	Value
Stator length	240 mm
Permanent magnet length	30 mm
Permanent magnet width	24 mm
Permanent magnet height	6.5 mm
Permanent magnet material	NdFeB
Number of permanent magnets	64
Air-gap width	9 mm
Pole pitch	30 mm
Remanence	1.31 T

In this study, according to the severity of PMSLM air-gap nonuniformity fault, each type of air-gap nonuniformity fault dataset is divided into three fault severity levels, namely light, moderate, and severe faults, at a ratio of 2:3:5. Therefore, the four types of air-gap nonuniformity faults correspond to a total of 12 classification labels, as listed in Table 2.

Table 2. Air-gap nonuniformity fault labels and degree.

Fault type	Degree of fault		
	0~1.0 mm (light)	1.0~2.5 mm (moderate)	2.5~5.0 mm (severe)
Left	T01	T02	T03
Right	T04	T05	T06
Up	T07	T08	T09
Down	T10	T11	T12

In this study, JMAG software is used to establish high-precision finite element models of the PMSLM under different fault conditions, and the corresponding external magnetic field signals are obtained. During the simulation, 3-D finite element models with different degrees of air-gap nonuniformity ranging from 0 to 5 mm are constructed at an interval of 0.01 mm. The corresponding external magnetic field signal data are then collected for feature extraction and classification by the proposed method. Figure 2 shows the 3-D finite-element model of the PMSLM, including the magnetic field distribution

and external magnetic field signal. Figure 3 shows various fault signals under different degrees of air-gap nonuniformity.

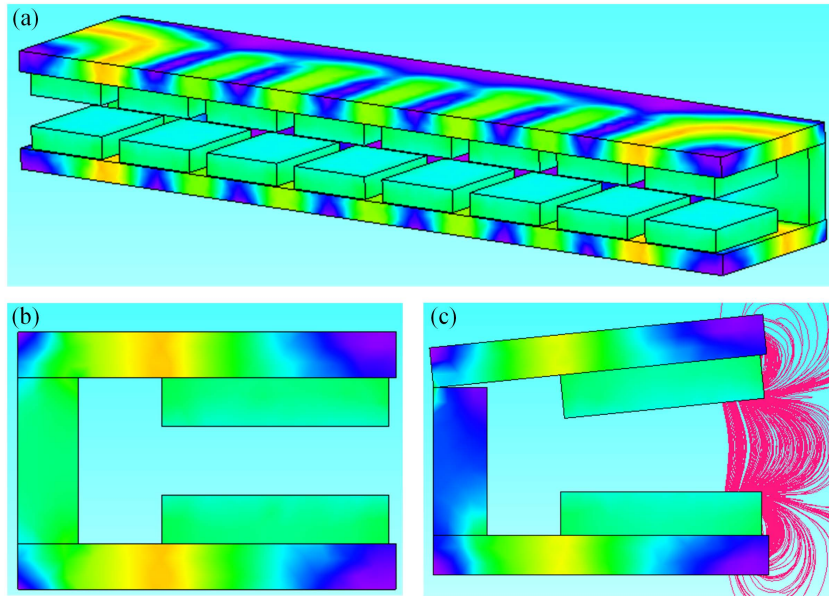


Figure 2. 3-D finite-element model of the PMSLM. **(a)** Magnetic field distribution; **(b)** Side view of the magnetic field distribution; **(c)** Side view of the external magnetic field signal.

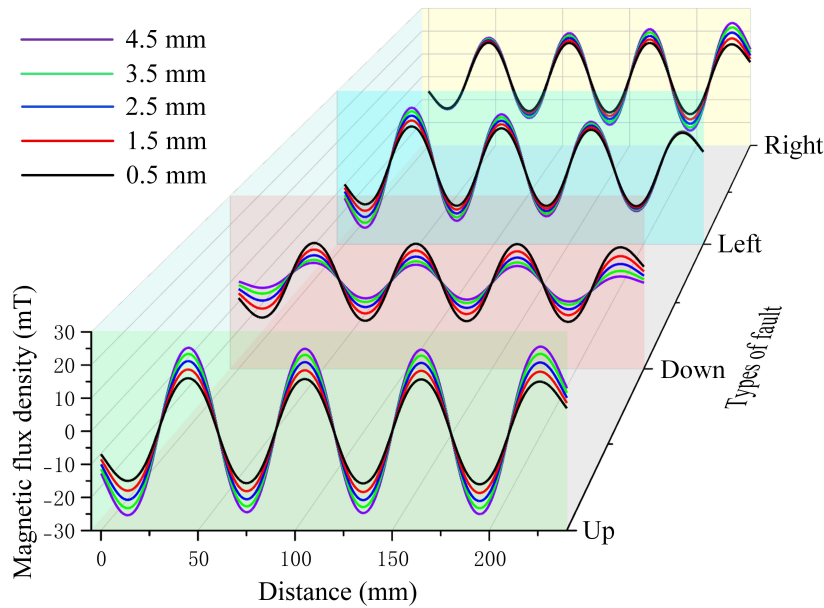


Figure 3. Air-gap nonuniformity fault curve.

3. Theoretical analysis of the network model

3.1. Hankel matrix image

The Hankel matrix transformation is a structured signal-embedding method that maps a 1-D sequence into a 2-D matrix by arranging overlapping subsequences in a prescribed manner [26]. Its applications include time-series analysis, signal feature extraction, and fault diagnosis. In this work, the Hankel

embedding converts each external-field waveform into the grayscale pattern shown in Figure 4. This representation exposes spatial structures and textures that can be analyzed by the image branch.

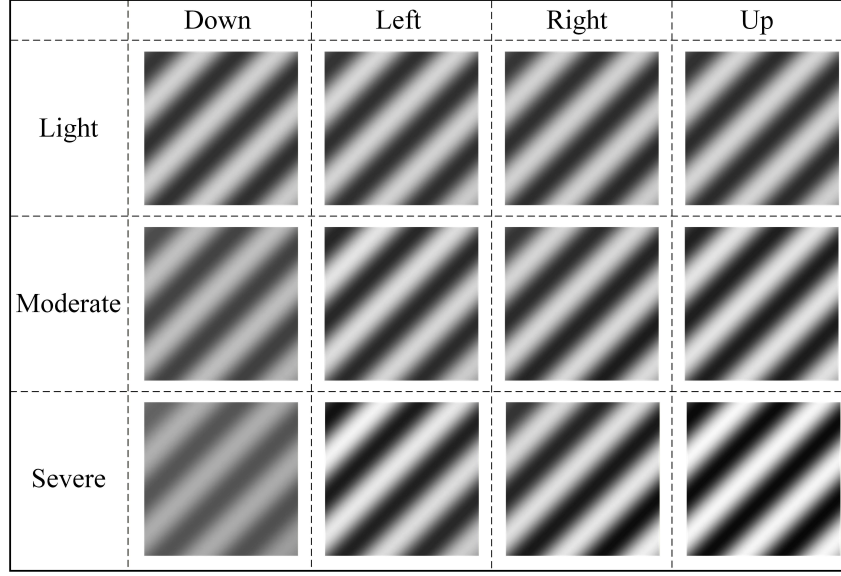


Figure 4. Hankel matrix images.

For an arbitrary discrete 1-D signal of length N , e.g., $x = [x(1), x(2), \dots, x(N)]^T$, the standard Hankel matrix $H \in \mathbb{R}^{m \times n}$ can be constructed as follows:

$$H = \begin{bmatrix} x(1) & x(2) & \cdots & x(n) \\ x(2) & x(3) & \cdots & x(n+1) \\ \vdots & \vdots & \vdots & \vdots \\ x(m) & x(m+1) & \cdots & x(m+n-1) \end{bmatrix} \quad (1)$$

where m denotes the number of matrix rows, or equivalently the number of sliding windows, n denotes the number of matrix columns, or equivalently the window length, and $m + n - 1 = N$ [27]. As can be seen from the above equation, the matrix is constructed using a sliding window with a stride of 1. Therefore, this transformation can preserve the local continuity of the original sequence in a highly overlapping manner. Meanwhile, the same sampling point repeatedly appears along the anti-diagonals of the matrix [28], allowing local fluctuations, periodic disturbances, and subtle fault-related morphological differences to be transformed into 2-D structured textures, thereby providing richer spatial information for the 2-D branch network.

To further convert the Hankel matrix into a single-channel grayscale image, the matrix elements are normalized according to the value range of the Hankel matrices in the training set. Let P_{low} and P_{high} denote the lower and upper percentile levels, respectively, with baseline values of 0.5% and 99.5%. The corresponding numerical bounds, v_{low} and v_{high} are estimated from the Hankel matrix elements of the clean training set in each fold. These bounds are then applied unchanged to the training, noise-free test, and noisy test samples. The normalized Hankel matrix $G \in [0, 1]^{m \times n}$ can then be expressed as follows:

$$G(i, j) = \text{clip} \left(\frac{H(i, j) - v_{\text{low}}}{v_{\text{high}} - v_{\text{low}}}, 0, 1 \right) \quad (2)$$

where $H(i, j)$ represents the entry of the Hankel matrix located at row i and column j , while $G(i, j)$ represents the corresponding normalized grayscale intensity value, and $\text{clip}(\cdot)$ is used to constrain the value within the range of $[0, 1]$. Subsequently, G is linearly scaled to $[0, 255]$, and converted into an 8-bit grayscale matrix $I_{8\text{-bit}} \in \{0, 1, \dots, 255\}^{m \times n}$. Finally, to reduce the geometric distortion caused by resizing a non-square Hankel grayscale matrix and to meet the fixed input-size requirement of the 2-D branch network, edge-replication padding is first applied to convert it into a square image, which is then resized to the fixed input size required by the 2-D branch network:

$$I = \text{Resize}(\text{Pad}(I_{8\text{-bit}})) \in \mathbb{R}^{1 \times S \times S} \quad (3)$$

where $\text{Pad}(\cdot)$ and $\text{Resize}(\cdot)$ denote the padding and size normalization operations, respectively. I denotes the final single-channel Hankel grayscale image fed into the 2-D branch network, and S denotes the side length of the input image for the 2-D branch network.

3.2. The architecture of LD-JDNet

In this study, LD-JDNet consists of a 1-D signal branch and a 2-D image branch. As illustrated in Figure 5, LD-JDNet takes two representations of the same fault sample as inputs: the original external magnetic field signal is fed into the 1-D branch, whereas the corresponding Hankel grayscale image is fed into the 2-D branch. The two branches independently perform feature extraction and classification mapping to generate their respective unnormalized class scores, which are subsequently fed into the decision layer to generate the final class logits, thereby yielding the final fault diagnosis result.

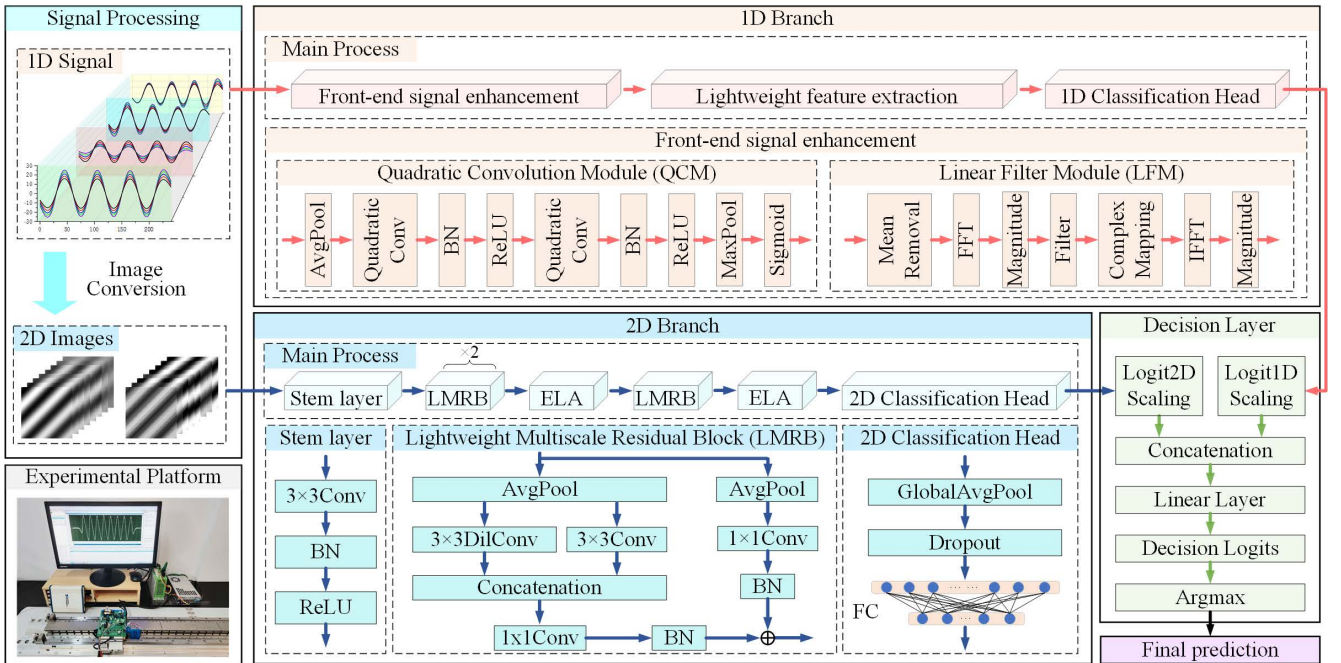


Figure 5. Schematic diagram of the overall workflow.

3.2.1. 1-D feature extraction branch

External magnetic field signals are typically characterized by subtle interclass differences, weak local features, and high susceptibility to environmental noise. Therefore, effective fault feature extraction

from 1-D magnetic field signals is a key issue for improving the diagnostic accuracy and robustness of air-gap nonuniformity fault diagnosis in PMSLM.

Figure 5 illustrates the architecture of the 1-D branch, which integrates a front-end signal enhancement module with a lightweight feature extractor. This design improves the extraction of fault-related features from the original magnetic field signals while maintaining low model complexity. Specifically, the front-end signal enhancement component comprises a quadratic convolution module and a linear filtering module [29], whereas the lightweight feature extraction component consists of a wide-kernel convolution and lightweight multiscale residual blocks.

First, the input signal is enhanced by the quadratic convolution module. Let the input 1-D signal be $x \in \mathbb{R}^{B \times 1 \times L}$, where B denotes the batch size and L denotes the signal length. After quadratic convolution processing, x can be expressed as:

$$Q(x) = \text{Conv}(x) \odot \text{Conv}(x) + \text{Conv}(x \odot x) \quad (4)$$

where $\text{Conv}(\cdot)$ denotes the 1-D convolution operation, $\odot$ denotes element-wise multiplication. Compared with ordinary linear convolution, quadratic convolution introduces multiplicative and squared terms, thereby enhancing the representation capability for nonlinear local variations in the signal. This is beneficial for highlighting weak disturbance features caused by air-gap nonuniformity fault. In this study, the input signal $x_i \in \mathbb{R}^{B \times 1 \times L}$ is processed by two consecutive quadratic convolutions to obtain the enhanced signal $\tilde{x}_q$:

$$x_q = Q\left(\text{ReLU}\left(\text{BN}\left(Q(x_i)\right)\right)\right) \quad (5)$$

Subsequently, the output is processed by batch normalization (BN), ReLU, and sigmoid activation functions to obtain the enhanced signal x_q . The signal x_q is then fed into the linear filter module and processed using the Fast Fourier Transform (FFT), yielding:

$$x_f = \left| \text{FFT}\left(x_q - \overline{x_q}\right) \right| \quad (6)$$

The signal x_f is first processed by a linear mapping and then converted back to the time domain through the Inverse Fast Fourier Transform (IFFT), yielding the front-end-enhanced signal x_e :

$$x_e = \left| \text{IFFT}\left(W_f x_f + b_f\right) \right| \quad (7)$$

where W_f and b_f denote the learnable weight and bias, respectively.

The front-end enhanced signal is then fed into the lightweight feature extraction module. As shown in Figure 6, the front part of this module is a wide-kernel convolution, where a large convolution kernel with a size of 49 is applied to local signal segments. Preliminary downsampling is further performed through a convolution with a stride of 4 and average pooling (AvgPool):

$$\begin{cases} Z'_0 = \left(\text{BN}\left(\text{Conv}(x_e)\right)\right) \\ Z_0 = \text{AvgPool}\left(\text{ReLU}(Z'_0)\right) \end{cases} \quad (8)$$

The lightweight multiscale residual block consists of multiscale depthwise convolution branches and a small-convolution residual branch. For the input feature Z_0 , layer normalization (LN) is first performed, followed by a transpose operation to obtain Z_1 . Then, depthwise convolutions with different dilation rates are employed to extract signal features at multiple scales. In this way, local detailed features and long-range spatial correlation features can be extracted while maintaining a low parameter count, thereby enhancing the multiscale representation capability of the 1-D signal:

$$H_i = \text{SiLU}\left(\text{BN}\left(\text{DWConv}_d(Z_1)\right)\right) \quad (9)$$

where $i = 1, 2, 3$, $d = 1, 2, 4$. The three branch-specific features H_1 , H_2 and H_3 are stacked channel-wise and subsequently projected through a 1×1 convolution, yielding the integrated multiscale feature Z_2 :

$$Z_2 = \text{Conv}_{1 \times 1}\left(\text{Concat}\left[H_1, H_2, H_3\right]\right) \quad (10)$$

Z_2 is sequentially processed by BN, SiLU activation, and dropout, and is then transposed to obtain Z_3 . The residual connection is used to alleviate information attenuation during deep feature extraction and improve the training stability of the model. On this basis, the small-convolution residual branch further refines local neighborhood responses using a small convolution with a kernel size of $k = 3$:

$$Z_r = Z_3 + Z_0 + \text{Dropout}\left(\text{ReLU}\left(\text{BN}\left(\text{Conv}_{k=3}(Z_3 + Z_0)\right)\right)\right) \quad (11)$$

In this study, the above lightweight multiscale residual block is stacked twice to enhance the model's ability to extract fault features at different scales. Finally, the extracted features are sequentially processed by LN and global average pooling (GAP), implemented using adaptive average pooling with an output size of 1, followed by a fully connected classifier that generates the unnormalized discriminative scores for all classes:

$$\begin{cases} g = \text{GAP}\left(\text{LN}(Z_r)\right) \\ o = \text{FC}\left(\text{Dropout}(g)\right) \end{cases} \quad (12)$$

where $o \in \mathbb{R}^{B \times K}$ denotes the class logits, and K is the number of fault categories.

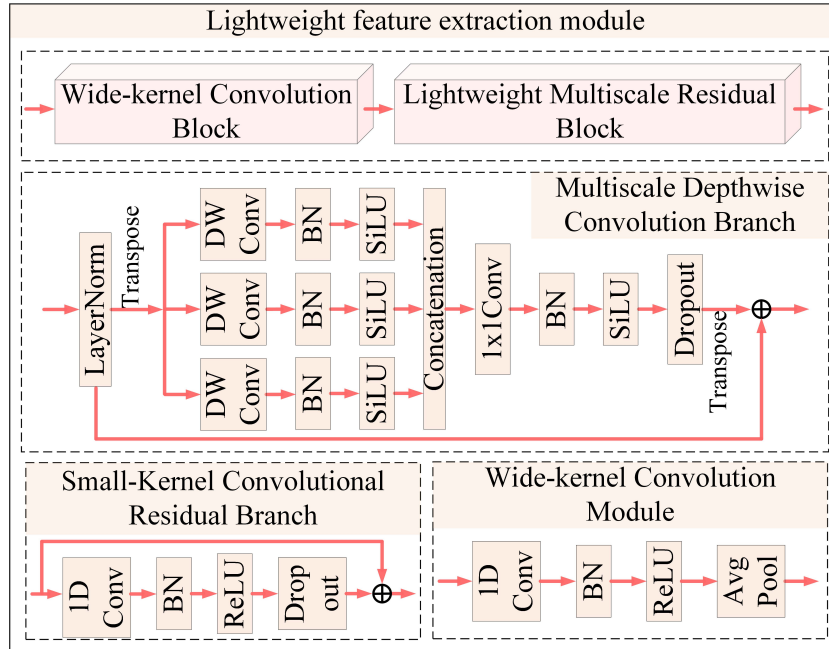


Figure 6. Lightweight feature extraction module.

3.2.2. 2-D branch feature extraction architecture

The Hankel matrix transformation converts local fluctuations and fault-induced morphological differences in 1-D magnetic-field signals into structured spatial textures. Consequently, 2-D Hankel grayscale images provide additional spatial structural and multiscale texture information, which facilitates the discrimination

of similar fault categories and improves model robustness under noise interference. Therefore, effectively extracting spatial structural and texture features from 2-D Hankel images is equally important for complementing the waveform information captured by the 1-D branch and enhancing the discrimination of similar fault categories under noisy conditions. Based on the above analysis, a dedicated 2-D branch is designed to extract multiscale spatial structural features and fault-related texture information from Hankel grayscale images. This branch consists of a stem layer, multiscale residual feature extraction stages, ELA modules, and a classification head. Its main architecture is illustrated in Figure 5.

Let the input Hankel grayscale image be $X \in \mathbb{R}^{1 \times H \times W}$. The 2-D branch first performs shallow feature mapping through the stem layer:

$$F_0 = \text{ReLU}(\text{BN}(\text{Conv}_{3 \times 3}(X))) \quad (13)$$

where $\text{Conv}_{3 \times 3}(\cdot)$ denotes a 2-D convolution operation with a kernel size of 3. No downsampling is applied in this layer, and thus the spatial resolution of the input feature remains unchanged. This design is used to preserve the early texture and grayscale distribution information in the Hankel image. Subsequently, the feature F_0 is sequentially fed into three multiscale residual stages. Each stage contains one lightweight multiscale residual block (LMRB). Spatial downsampling and channel expansion are performed at the start of the stage. Figure 5 shows the detailed structure of the LMRB. For the input feature F_{s-1} of the s -th stage, the main branch first performs average-pooling downsampling, yielding

$$\tilde{F}_{s-1} = \text{AvgPool}(F_{s-1}), \quad s = 1, 2, 3 \quad (14)$$

Subsequently, the module employs a standard 3×3 convolution branch and a dilated 3×3 convolution branch to extract local detailed features and features with a larger receptive field, respectively:

$$\begin{cases} B_1 = \text{ReLU}(\text{BN}(\text{Conv}_{3 \times 3}(\tilde{F}_{s-1}))) \\ B_2 = \text{ReLU}(\text{BN}(\text{Conv}_{3 \times 3}^d(\tilde{F}_{s-1}))) \end{cases} \quad (15)$$

where $\text{Conv}_{3 \times 3}^d(\cdot)$ represents a 3×3 convolution configured with a dilation factor of d . After the outputs of the two branches are concatenated along the channel dimension, a 1×1 convolution is used for channel fusion:

$$U_s = \text{BN}(\text{Conv}_{1 \times 1}(\text{Concat}(B_1, B_2))) \quad (16)$$

Furthermore, during downsampling, a residual branch consisting of average pooling followed by a 1×1 convolution is adopted to achieve spatial size reduction and channel matching, rather than directly using strided convolution for downsampling:

$$R_s = \text{BN}(\text{Conv}_{1 \times 1}(\tilde{F}_{s-1})) \quad (17)$$

This design reduces the feature-map resolution and mitigates high-frequency noise aliasing. These effects help improve model stability under noisy conditions. Therefore, the output of the lightweight multiscale residual stage is given by:

$$F_s = \text{ReLU}(U_s + R_s) \quad (18)$$

To enhance the utilization of salient spatial information in 2-D Hankel grayscale images while controlling the parameter count and computational complexity, the ELA mechanism [30] is introduced into the 2-D feature extraction network. Figure 7 shows ELA, a lightweight spatial attention mechanism.

Unlike channel attention mechanisms such as efficient channel attention [31], ELA uses directional attention to highlight key spatial regions.

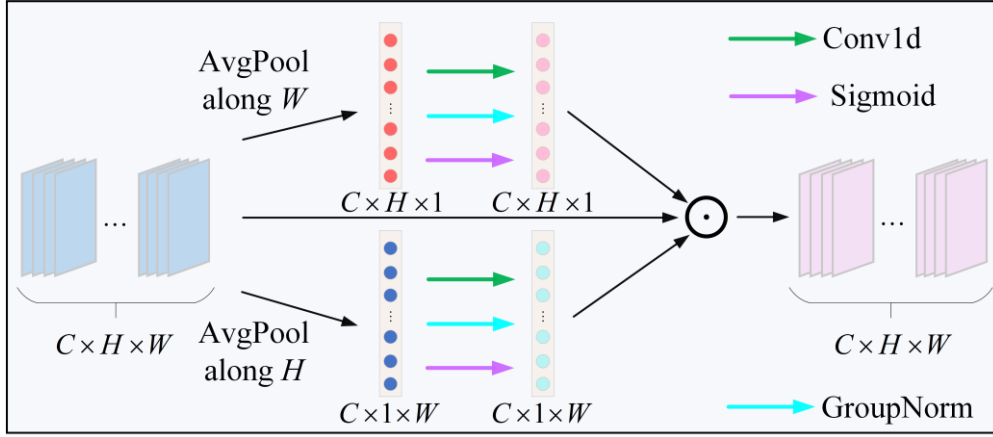


Figure 7. ELA architecture diagram.

Let the input feature map be denoted as $X \in \mathbb{R}^{C \times H \times W}$, where C , H , and W represent the number of feature channels, feature-map height, and feature-map width, respectively. First, average pooling is performed along the height and width dimensions to obtain the width-direction feature vector $Z^w \in \mathbb{R}^{C \times 1 \times W}$ and the height-direction feature vector $Z^h \in \mathbb{R}^{C \times H \times 1}$ respectively. This directional pooling operation averages the responses in each row or column within each channel. It preserves positional information along the other spatial direction and generates two 1-D spatial feature vectors. Subsequently, 1-D depthwise convolutions process Z^h and Z^w separately. Each convolution uses a kernel size of 5 to capture correlations between adjacent positions. Since the number of convolution groups is equal to the number of input channels, channel-wise 1-D convolution is employed to extract spatial features along the two directions without introducing additional channel compression. The convolution outputs are further processed by group normalization and sigmoid activation to generate the height-direction attention weight A^h and width-direction attention weight A^w . The final output Y is expressed as:

$$Y = X \odot A^h \odot A^w \quad (19)$$

through this operation, ELA enhances the key texture and structural regions associated with different fault categories while suppressing irrelevant background responses.

ELA extracts positional information along different spatial directions of the feature map and employs 1-D depthwise convolutions to capture correlations between adjacent positions. Considering that shallow features tend to contain more noise and irrelevant textures, ELA modules are placed after the second and third stages of the network, with channel counts of 128 and 256, respectively. The two modules add 896 and 1792 parameters, respectively, totaling 2688 parameters. The attention weights from the two spatial directions jointly modulate the input features. This modulation helps the network focus more effectively on texture and structural regions in 2-D Hankel images. These regions are associated with air-gap nonuniformity faults. It also reduces the influence of background noise and irrelevant information. Moreover, ELA employs channel-wise 1-D convolutions without requiring complex channel compression and expansion operations. Therefore, it enhances fault feature extraction. This is achieved with only a small increase in computational cost and the number of model parameters.

As shown in Figure 8, to illustrate the spatial reweighting performed by the two directional pathways of ELA, one test sample was selected from each of the 12 fault categories, and the second ELA module located after Stage 3 in the trained 2-D branch was visualized under the 20 dB condition. From left to right, the columns show the input Hankel image, the height-direction and width-direction attention weights, the combined attention weights, the feature responses before and after ELA, and the activation retention ratio. The retention ratio is calculated by dividing the interpolated post-ELA response map by the interpolated pre-ELA response map. The height-direction and width-direction attention maps reveal nonuniform weighting along their respective spatial coordinates. Their product is computed channel-wise to form a spatial gating tensor, whose channel average is displayed as the combined attention map. In several selected examples, including T05, T08, and T11, some anti-diagonal feature structures exhibit relatively higher retention than the surrounding regions. These observations provide direct intermediate visual evidence for the spatially selective feature reweighting performed by ELA.

Finally, the 2-D branch employs global average pooling to compress the final-layer feature map into an image-level feature vector g_{2D} . After Dropout regularization, the feature vector is fed into a linear classifier to obtain the class logits of the 2-D branch:

$$z_{2D} = W_{2D} \text{Dropout}(g_{2D}) + b_{2D} \quad (20)$$

where W_{2D} represents the classifier's weight matrix, while b_{2D} corresponds to its bias term. $z_{2D} \in \mathbb{R}^K$ represents the unnormalized class scores output by the 2-D branch, $K = 12$. Therefore, the 2-D branch can extract multiscale spatial structural features from the Hankel fault images and provide complementary information to the 1-D branch, thereby supplying effective 2-D discriminative information for the subsequent joint linear decision process.

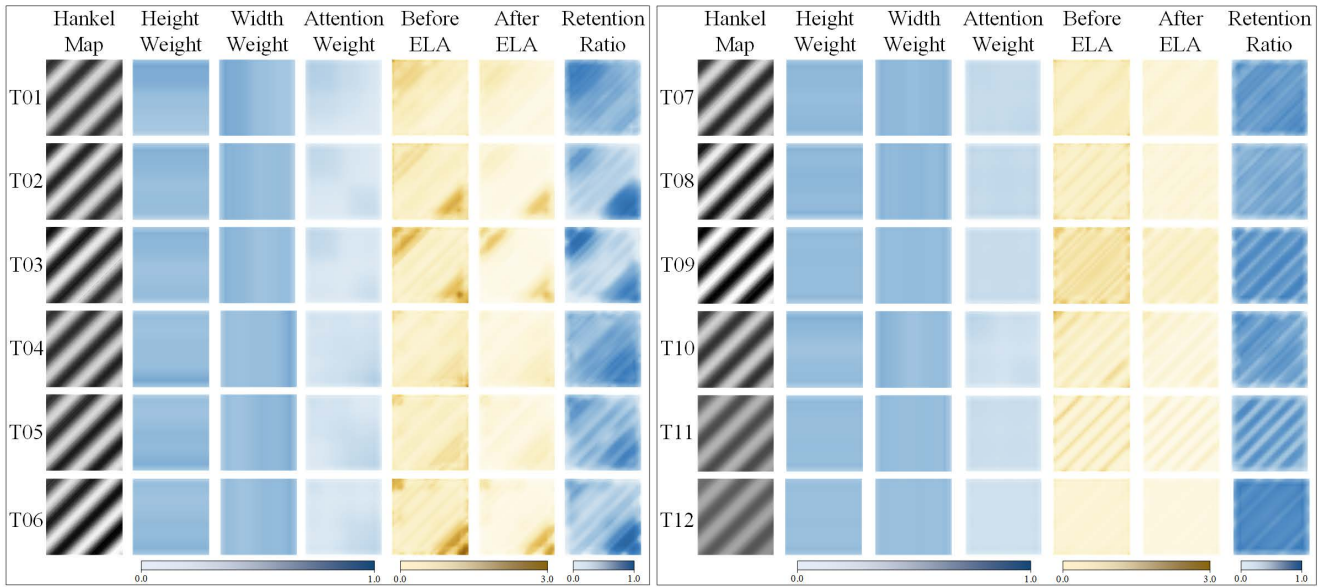


Figure 8. Heatmap visualization of the ELA module.

3.2.3. Joint linear decision strategy

To fully exploit the complementary discriminative capabilities of the 1-D signal branch and the 2-D image branch, a joint linear decision layer is constructed after the two branches. The proposed method

does not directly select between the labels predicted by the two branches or assign either branch higher decision priority in advance. It first rescales the class logits from both branches. A learnable linear mapping then produces the final fault diagnosis result. The specific procedure is described as follows.

For the i -th input sample, the 1-D and 2-D branches output the corresponding class logits z_i^{1D} and z_i^{2D} , respectively. The two diagnostic branches use different network architectures and feature extraction mechanisms. Their output logits may therefore have different numerical scales. Therefore, learnable parameters are introduced to proportionally rescale the logits of the two branches, respectively:

$$\dot{z}_i^m = \frac{z_i^m}{T_m} \quad (21)$$

where $m \in \{1D, 2D\}$, $T_m > 0$ denotes the adjustment parameter corresponding to branch (m), and $\dot{z}_i^m$ represents the adjusted logits. When $T_m > 1$, the numerical differences among the class logits are compressed; when $0 < T_m < 1$, these differences are amplified. This proportional adjustment preserves the relative ordering of class logits within each branch and therefore generally leaves the predicted class unchanged. Its main purpose is to align the numerical scales of the outputs from the two branches. This alignment makes the discriminative information more comparable. The aligned information is then used in the joint decision process.

After magnitude rescaling, the outputs of the two branches are combined along the feature dimension. This produces the joint decision feature h_i . Compared with using only the predicted labels or maximum class probabilities of the two branches, this operation preserves their response information for all fault categories, allowing the relationships among different class scores to be exploited to correct predictions for easily confused fault categories. Subsequently, the joint decision feature is fed into a trainable fully connected linear layer to obtain the final decision logits:

$$z_i^D = Wh_i + b \quad (22)$$

where $z_i^D \in \mathbb{R}^K$ denotes the final joint decision logit vector, $K=12$, W is the learnable weight matrix, and b is the bias vector. Finally, the class with the highest score in the decision logits is selected as the fault diagnosis result.

Accordingly, the proposed joint linear decision layer offers three main advantages: (1) the learnable scale-adjustment parameters reduce the differences in logit magnitudes caused by the heterogeneous architectures of the two branches, thereby improving the comparability of their outputs; (2) the concatenation of the complete logit vectors preserves the responses of both branches to all fault categories, which facilitates the complementary discrimination of easily confused fault categories; and (3) the trainable linear mapping models the relationships both between the two branches and among different fault categories, thereby enabling a more comprehensive joint decision than fixed-weight averaging or voting-based schemes.

4. Analysis of simulation classification results

4.1. Simulation experimental setup

In this section, simulation experiments are conducted to validate the proposed method. All experiments are performed under the Windows 11 operating system on a computing platform equipped with an AMD

Ryzen 5 5600X processor, an NVIDIA GeForce RTX 4080 SUPER GPU, and 64 GB of memory. All methods were implemented in Python 3.7 using the PyTorch 1.12 framework. LD-JDNet is trained in stages. The 1-D and 2-D branches are trained independently for 300 epochs using the AdamW optimizer and cross-entropy loss, with an initial learning rate of 1×10^{-3} , a batch size of 32, and a weight decay of 1×10^{-4} . A cosine annealing schedule is applied with a minimum learning rate of 1×10^{-6} . After branch training, the parameters of both branches are frozen. The scale-adjustment parameters are optimized separately using L-BFGS with a learning rate of 0.1 and a maximum of 100 iterations. Subsequently, the joint linear decision layer is trained using AdamW and cross-entropy loss, with an initial learning rate of 1×10^{-2} , a batch size of 128, and a weight decay of 1×10^{-4} . Cosine annealing is also applied during this stage. The maximum number of training epochs is set to 300.

The diagnostic capability of LD-JDNet is assessed through comparative experiments with four representative models, including MSResNet [32], MCSwinT [33], ResNeSt50 [34] and MobileNetV4-M [35]. Among them, MSResNet and MCSwinT are 1-D models, whereas ResNeSt50 and MobileNetV4-M are 2-D models. Accuracy, precision, and F1-score are adopted as the evaluation metrics. For the multiclass classification task, each class is successively regarded as the positive class, while all remaining classes are regarded as negative classes. For each class, the numbers of true positives, false positives, false negatives, and true negatives are determined and subsequently used to compute the evaluation metrics [36].

4.2. Analysis of simulation experimental results

To reduce the randomness introduced by a single data split and prevent overlap between the training and test samples, five-fold cross-validation is employed in this section to evaluate the proposed model and the comparison models. The comparative study evaluates LD-JDNet and the comparison models from three different perspectives: classification performance under noise-free conditions, noise robustness at different signal-to-noise ratios (SNRs), and model computational complexity. All models use the same data partitioning strategy and evaluation criteria.

Corresponding ablation studies are conducted to systematically evaluate the contributions and complementarity of the two diagnostic branches under different noise conditions by retaining only the 1-D branch or the 2-D branch. As shown in Table 3, the complete model achieves an accuracy of 99.83% under noise-free conditions. This accuracy is 0.50 and 1.16 percentage points higher than those of the 1-D and 2-D branches, respectively. Under stronger noise interference at 20 dB, the complete model maintains 93.53% accuracy. The corresponding gains over the 1-D and 2-D branches are 2.70 and 0.56 percentage points, respectively. The complete model also achieves the highest accuracy at 40 and 30 dB. The 1-D branch performs better under noise-free and weak-noise conditions. However, the 2-D branch is more robust at lower signal-to-noise ratios. These results show that waveform information from the 1-D branch and spatial texture information from the 2-D branch are complementary. Their joint use allows the complete model to outperform either branch alone across the evaluated noise levels.

Table 4 presents the classification results of all methods on the noise-free test set. This study involves a multiclass classification task. Accuracy, precision, and F1-score are used as the evaluation metrics. Table 4 shows that LD-JDNet achieves an accuracy, precision, and F1-score of 99.83%, 99.84%, and 99.83%, respectively. These results demonstrate its superior overall performance. Compared with MSResNet, MCSwinT, and ResNeSt50, the proposed method improves the accuracy by 0.20, 0.23, and 0.56 percentage points, respectively. It also outperforms MobileNetV4 by 0.06 percentage points in

terms of accuracy. All models achieve high classification accuracy under noise-free conditions. However, the proposed method performs better overall in terms of accuracy, precision, and F1-score.

Table 3. Ablation study of the proposed method under different noise conditions. Bold values indicate the best results for each metric.

Method	Accuracy (%)			
	No noise	40 dB	30 dB	20 dB
Proposed	99.83	99.67	98.27	93.53
2-D branch	98.67	98.40	97.53	92.97
1-D branch	99.33	99.23	96.80	90.83

Table 4. Classification results of the proposed and comparative methods. Bold values indicate the best results for each metric.

Method	Accuracy (%)	Precision (%)	F1-Score (%)
Proposed	99.83	99.84	99.83
MSResNet	99.63	99.65	99.63
MCSwinT	99.60	99.61	99.60
ResNeSt50	99.27	99.29	99.27
MobileNetV4-M	99.77	99.77	99.77

Figure 9a presents the confusion matrix obtained using the proposed method under noise-free conditions. Most samples are concentrated along the main diagonal, indicating that the proposed method can accurately distinguish among different fault categories. The normalized confusion matrix shows that the misclassification rate from T08 to T07 is only 0.02, whereas all samples from the other fault categories are correctly identified.

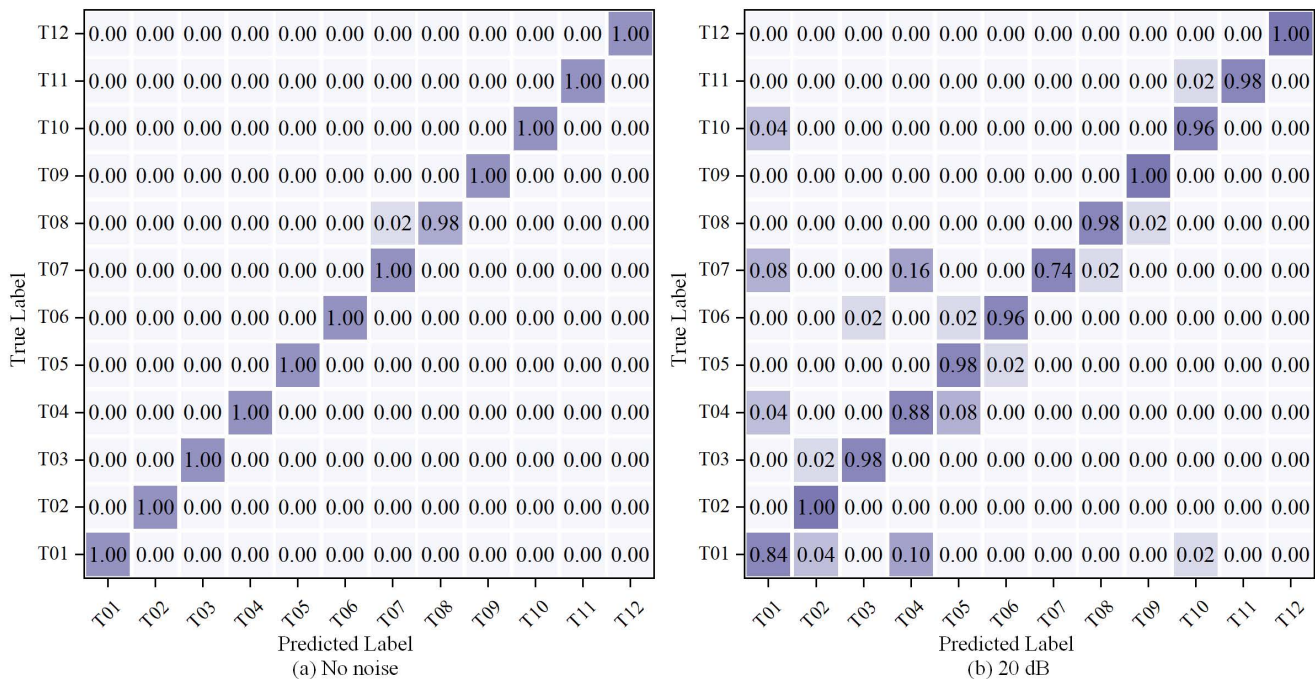


Figure 9. Confusion matrices of the proposed method. (a) No noise; (b) 20 dB.

To examine the diagnostic robustness under noisy conditions, white Gaussian noise at different SNRs is introduced only into the test set to simulate practical noisy environments and assess the anti-interference

capability and stability of the models. The SNRs are set to 40, 30, and 20 dB, and the experimental results are presented in Figure 10. The height of each bar represents the mean accuracy obtained from the five-fold experiments, while the error bars indicate the corresponding standard deviations.

To further examine the recognition performance of individual fault categories under strong noise interference, Figure 9b presents the confusion matrix of LD-JDNet at an SNR of 20 dB for the same test fold used in Figure 9a. Nine of the 12 categories achieve correct recognition rates of at least 96%. The rates for T01, T04, and T07 are 84%, 88%, and 74%, respectively. For T07, 16% and 8% of its samples are misclassified as T04 and T01, respectively. These results show that LD-JDNet maintains high recognition rates for most fault categories.

The classification accuracy of all models decreases to varying degrees as the SNR falls. Figure 10 shows that LD-JDNet achieves accuracies of 99.67%, 98.27%, and 93.53% at 40, 30, and 20 dB, respectively. Its accuracy drops by only 6.14 percentage points as the SNR decreases from 40 to 20 dB. In contrast, several comparison models exhibit more pronounced performance degradation as the noise intensity increases. These results demonstrate that LD-JDNet maintains high classification accuracy and stable diagnostic performance under noisy conditions, indicating its strong robustness against noise interference.

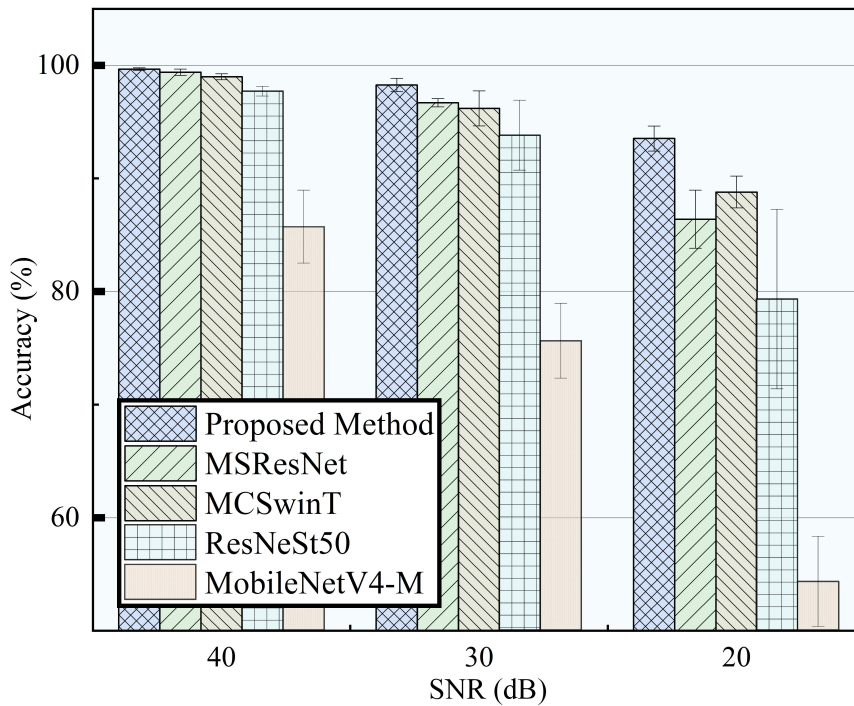


Figure 10. Robustness comparison results.

Furthermore, Table 5 lists the parameter count and single-sample inference times of the different models. The results demonstrate that the proposed model combines a low parameter count with high inference efficiency. Therefore, while ensuring high diagnostic accuracy and strong noise robustness, the proposed method effectively reduces computational complexity and achieves a favorable balance between accuracy and efficiency, thereby providing a basis for its subsequent deployment on resource-constrained edge computing devices.

Table 5. Comparison of parameter count and inference time of different methods. Bold values indicate the best results for each metric.

Method	Parameters (M)	Inference time (ms)
Proposed	0.54	5.83
MSResNet	2.12	7.52
MCSwinT	1.93	6.56
ResNeSt50	25.46	13.41
MobileNetV4-M	9.01	7.97

4.3. Sensitivity analysis of Hankel normalization percentiles

To examine the sensitivity to the Hankel normalization percentiles, P_{low} and P_{high} were independently perturbed by ± 0.1 and ± 0.2 percentage points around the baseline setting of (0.5%, 99.5%), yielding eight neighboring configurations. For each configuration, the normalization bounds were recalculated from the clean training data of each fold, and the corresponding Hankel images were regenerated. The 2-D branch, 1-D branch and the joint decision layer were retrained.

Classification performance and noise robustness were evaluated using the accuracy of the complete LD-JDNet under noise-free and 20 dB conditions. Feature distinctiveness was quantified using the silhouette score of the 256-dimensional features extracted after global average pooling and before the classifier of the 2-D branch. The score was calculated from all noise-free test samples in each fold using their ground-truth class labels and Euclidean distance. No additional feature normalization or dimensionality reduction was applied. Table 6 reports the mean and standard deviation across the five folds.

Table 6 presents the results for the eight neighboring configurations. Their mean accuracy ranges from 99.77% to 99.97% under noise-free conditions and from 93.33% to 94.17% at 20 dB. The corresponding baseline accuracies are 99.83% and 93.53%, respectively. The mean silhouette scores range from 0.5440 to 0.5609. These scores indicate similar feature distinctiveness across these configurations. The larger standard deviation of the (0.6%, 99.5%) configuration reflects greater variation across folds. These results indicate low local sensitivity to the normalization percentiles. High diagnostic performance is maintained across the tested neighboring settings.

Table 6. Sensitivity of LD-JDNet to Hankel normalization percentiles.

P_{low} (%)	P_{high} (%)	Noise-free accuracy (%)	Accuracy at 20 dB (%)	Silhouette score (noise-free)
0.3	99.5	99.83 $\pm$ 0.20	93.97 $\pm$ 1.06	0.5543 $\pm$ 0.0092
0.4	99.5	99.97 $\pm$ 0.07	93.87 $\pm$ 1.35	0.5559 $\pm$ 0.0096
0.6	99.5	99.77 $\pm$ 0.19	94.07 $\pm$ 0.68	0.5440 $\pm$ 0.0295
0.7	99.5	99.80 $\pm$ 0.22	93.33 $\pm$ 1.53	0.5557 $\pm$ 0.0092
0.5	99.3	99.80 $\pm$ 0.14	93.43 $\pm$ 0.45	0.5609 $\pm$ 0.0116
0.5	99.4	99.90 $\pm$ 0.15	93.77 $\pm$ 1.25	0.5550 $\pm$ 0.0069
0.5	99.6	99.93 $\pm$ 0.09	94.03 $\pm$ 1.24	0.5553 $\pm$ 0.0107
0.5	99.7	99.90 $\pm$ 0.15	94.17 $\pm$ 1.13	0.5528 $\pm$ 0.0126

5. Experimental verification

5.1. Prototype experimental validation

The experimental setup was constructed to further assess the effectiveness and diagnostic accuracy of the proposed method. Figures 11 and 12 show the setup used to acquire PMSLM air-gap nonuniformity fault data. The platform consists of the following components: (1) a motor prototype; (2) an NI USB-4431 data acquisition card; (3) a 3-D printed sensor bracket; (4) a computer; (5) PMSLM stator modules with different types of air-gap nonuniformity faults; (6) a hardware amplification circuit board for external magnetic field signals based on the AD620 chip; and (7) a tunneling magnetoresistance (TMR) sensor.

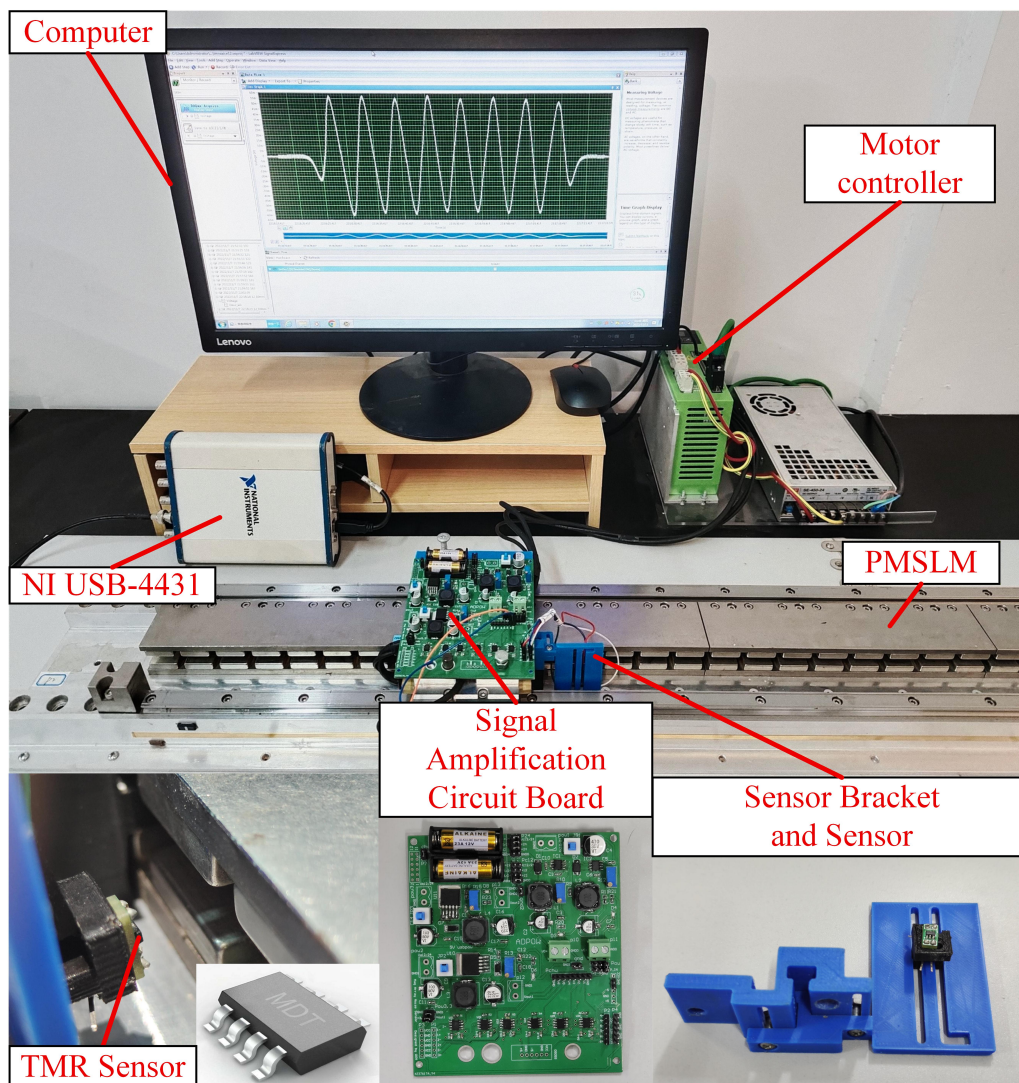


Figure 11. Experimental platform.

In this study, dynamic and static air-gap nonuniformity faults are preset by inserting feeler gauges with different thicknesses into the PMSLM stator. The detailed fault setting parameters are listed in Table 7. To collect fault signals, the TMR sensor is integrated on the motor mover. When the mover travels along the linear direction, the TMR sensor can collect external magnetic field signals at different positions along the guide rail. Finally, the sensor measurements are transferred to a computer via an NI data acquisition card and subsequently stored.

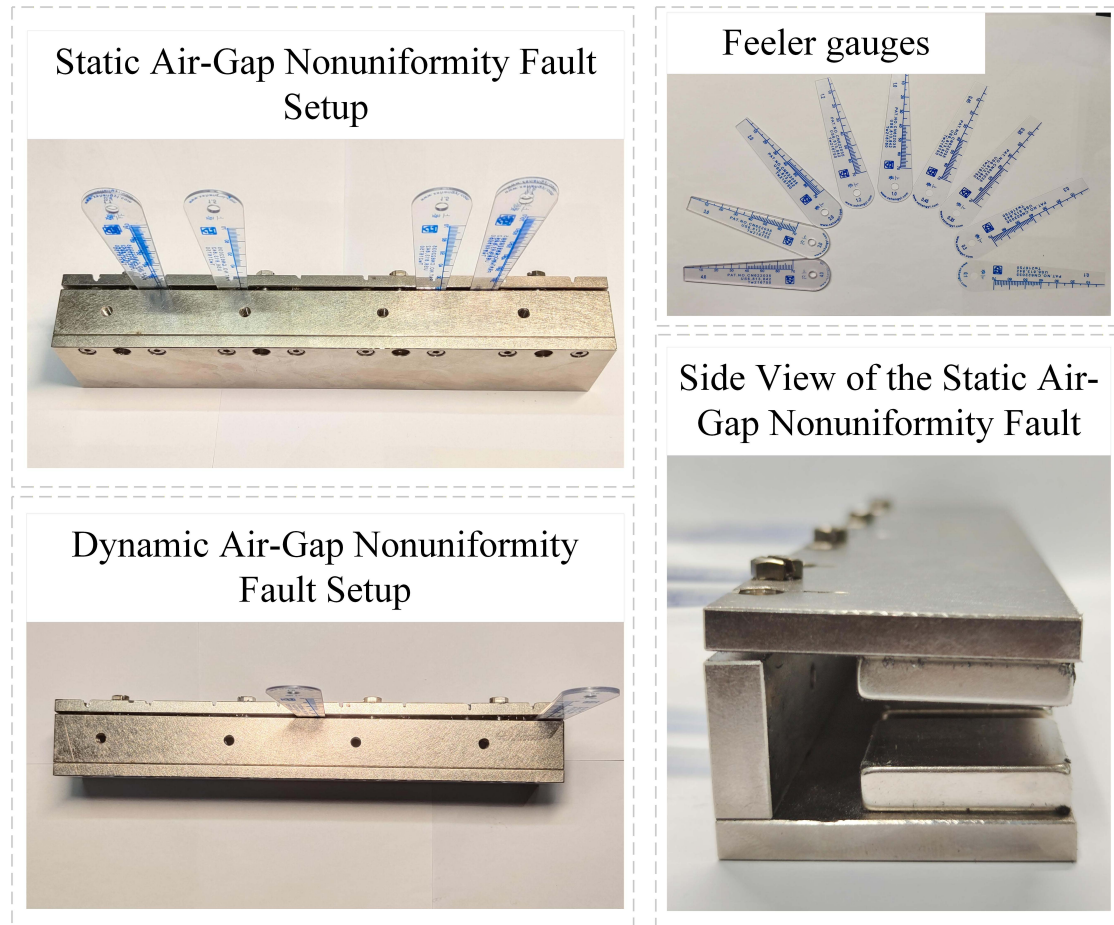


Figure 12. Preset air-gap nonuniformity fault conditions in the experiment.

To evaluate the performance and comparative advantages of LD-JDNet, noise with different intensities is added to the raw signals to simulate practical acquisition scenarios. Table 8 lists the diagnostic accuracy of each method. The proposed model achieves the highest recognition accuracy under all tested noise conditions. These results show that it can extract fault features effectively and reduce noise interference. The proposed method therefore achieves synergistic gains in accuracy and robustness. These gains demonstrate its novelty and application potential in air-gap nonuniformity fault diagnosis.

Table 7. Experiment air-gap nonuniformity fault preset.

Fault type		Fault degree (mm)		
Dynamic	Left	0.4	1.5	3
	Right	0.4	1.5	3
Static	Up	0.6	2	3.5
	Down	0.6	2	3

Table 8. Comparison of diagnostic accuracy on measured data under different noise conditions.

Method	Accuracy (%)		
	40 dB	30 dB	20 dB
Proposed	100.00	100.00	96.67
MSResNet	100.00	100.00	81.67
MCSwinT	100.00	95.00	83.33
ResNeSt50	98.33	88.33	81.67
MobileNetV4-M	75.00	60.00	46.67

5.2. Model deployment experimental validation

LD-JDNet was deployed on edge devices to further assess its potential for industrial use. The experiment evaluated the model's real-time performance and lightweight design. It also tested whether the model could be used in practice for fault diagnosis on edge devices. Figure 13 shows the Raspberry Pi 4B and NVIDIA Jetson Orin NX edge computing platforms used in the experiment. The Raspberry Pi 4B uses a Broadcom BCM2711 processor with a quad-core Cortex-A72 CPU. The CPU is based on the 64-bit ARMv8-A instruction set architecture and has a maximum clock frequency of 1.8 GHz. The NVIDIA Jetson Orin NX includes an NVIDIA Ampere-architecture GPU with 1024 CUDA cores and an eight-core Arm Cortex-A78AE CPU. Its CPU uses the 64-bit ARMv8.2 instruction set architecture, and the platform has 16 GB of LPDDR5 memory.

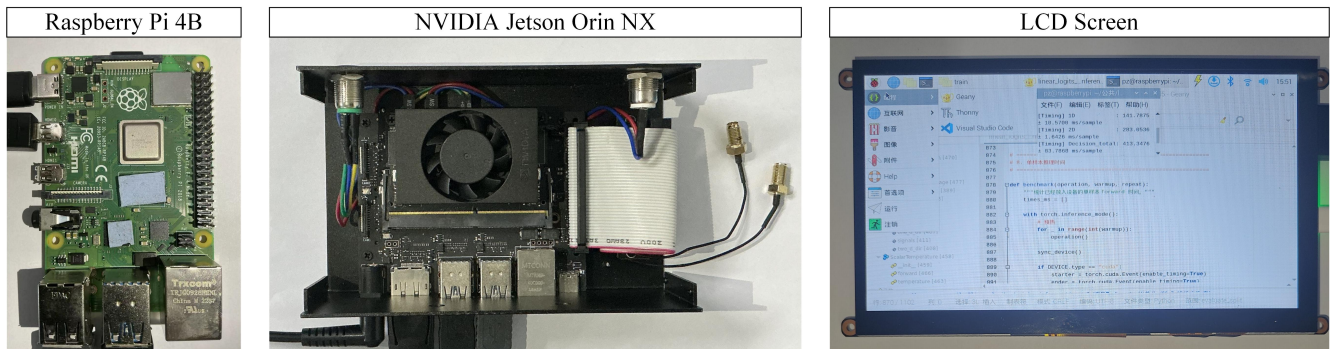


Figure 13. Edge deployment platforms and display interface.

The experimental results show a single-sample inference time of 384.22 ms on the Raspberry Pi 4B. This time drops to 16.92 ms on the more powerful NVIDIA Jetson Orin NX, showing high inference efficiency. These results confirm the method's lightweight design and suitability for deployment. They also show its feasibility and practical potential for real-time intelligent monitoring in industrial environments with limited resources.

5.3. Limitations and future work

This study validates LD-JDNet only under single air-gap nonuniformity fault conditions. In the experiments, these faults were introduced by adjusting the stator position with feeler gauges. Strong magnetic attraction makes it harder to repeatedly adjust and secure the double-sided permanent-magnet stator. Setting multiple fault components requires coordinated control of the stator displacement and inclination angle. Sufficient clearance must also be maintained for the mover to travel. These requirements make fault configurations difficult to reproduce and may increase the risk of contact between the mover and stator. Therefore, the current experimental platform has practical limitations. These limitations make it difficult to preset compound faults.

In future work, the fault-setting fixture will be improved, and simulated and measured datasets covering physically realizable combinations of air-gap nonuniformity faults and their severity levels will be constructed. A multi-label extension of LD-JDNet will be investigated. This will involve adjusting the fault label encoding and joint decision strategy. The extended model will then be tested under different noise conditions to assess its ability to identify concurrent faults.

6. Conclusion

This study proposes a lightweight dual-branch joint decision framework for air-gap nonuniformity fault diagnosis in PMSLMs. The 1-D branch extracts waveform variation information from the original external magnetic field signals. The 2-D branch extracts spatial texture information from the corresponding Hankel grayscale images. A joint linear decision strategy is then employed to make complementary use of these two types of discriminative information. Experiments show that the framework can distinguish air-gap nonuniformity faults of different types and severity levels. At an SNR of 20 dB, the method achieves a diagnostic accuracy of 93.53%. This result exceeds those of the selected comparison models and shows strong noise robustness. In addition, the model needs only 5.83 ms for single-sample inference and maintains high diagnostic accuracy. This indicates low computational overhead. Experiments on measured PMSLM data and deployment on edge computing platforms further support the framework's diagnostic reliability and practical applicability. The framework can also serve as a reference for condition monitoring and fault diagnosis of other electromechanical equipment. Such equipment includes rotating electrical machines. Future work will focus on improving fault feature extraction and model generalization under complex operating conditions and compound fault scenarios. This will help broaden the applicability of the proposed method in real-world industrial settings.

Data availability statement

No supplementary or additional data were generated in this study.

Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used generative AI tools only to improve language and readability. Specifically, the authors used ChatGPT for language polishing only for drafting in limited sections. The authors take full responsibility for the content of the manuscript.

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Authors' contribution

Conceptualization, X.L. and J.S.; methodology, X.L.; investigation, X.L. and J.S.; resources, S.L., J.S.; data curation, X.L.; writing—original draft preparation, X.L.; writing—review and editing, X.L., S.L. and J.S.; visualization, X.L.; supervision, S.L., J.S., Z.H. and Z.P.; project administration, S.L.; funding acquisition, S.L., J.S. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

There are no conflicts of interest to declare.

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