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BEARING FAULT DIAGNOSIS BASED ON DEEP LEARNING AND ARRAY STOCHASTIC RESONANCE UNDER STRONG NOISE BACKGROUND

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Abstract. *The diagnosis of bearing faults is important in the maintenance and running of industrial machinery. As the signal collection process is often interfered by noise, the accuracy of the diagnosis is reduced. Therefore, bearing fault diagnosis is always a challenging problem under strong noise background. This paper develops a new method that utilizes a combination of deep learning and array stochastic resonance to improve the robustness of models in the context of strong noise. By introducing a multi-branch dilated convolutional structure in the residual neural network, network performance is improved. However, the model may be disturbed and lead to performance degradation due to the presence of a strong noise background. To address this problem, an array stochastic resonance is introduced to help the network better explore the potential feature space during the training process. Array stochastic resonance enhanced the robustness of the network by introducing randomness to improve the accuracy. Experimental results show that our approach can dig deeper into defect features and has strong noise resistance. In a strong noise background with SNR of* -7 *dB, the accuracy can be more than 97.8%. It has a higher recognition performance compared to various deep learning algorithms. Compared to various deep learning algorithms, it has higher recognition performance.*

Keywords: Bearing fault diagnosis, Deep learning, Array stochastic resonance, Noise immunity

1. **Introduction.**

Bearings are critical components of rotating machinery, and its health status will directly affect the working performance of the equipment. However, during long-term operation, bearings are prone to failure due to harsh loading conditions. Timely detection of these faults is essential to prevent equipment damage. However, this process is often hampered by strong background noise in real industrial environments. This noise comes not only from the vibration of mechanical equipment, but also from the operating noise of other machinery, airflow noise and sensor measurement errors. Therefore, it is of great significance to develop methods that can effectively extract fault characteristics and improve diagnostic accuracy under strong noise background to ensure the stable operation of equipment [1, 2, 3, 4].

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The traditional fault diagnosis methods usually comprise three phases: data acquisition, feature extraction and classification. In terms of data acquisition, the vibration signal or sound signal of rotating mechanical equipment is usually collected. For these signals, features are extracted that help in fault identification. Finally, in the classification stage, fault diagnosis is carried out through traditional machine learning models, such as artificial neural network (ANN) [5], and support vector machine (SVM) [6]. However, the traditional data-based fault detection methods suffer from drawbacks such as feature dependence, heavy manual workload, information neglect and poor generalization [7, 8]. Under strong noise background, these problems become more pronounced, leading to reduced diagnostic effectiveness and an increased risk of missing potential defects.

Recently, as computer science develops rapidly, the wide deployment of deep learning in intelligent fault diagnosis and other fields has gradually become a trend [9, 10, 11, 12]. Deep learning explores and learns complex relationships hidden in the data by constructing deep neural networks and training them with volumes of fault data to achieve feature extraction and fault classification [13]. Compared to traditional methods, deep learning models are better able to adapt to noise diversity and significantly enhance diagnostic robustness under strong noise backgrounds, thanks to the advantage of end-to-end learning. For example, Zhou et al. [14] proposed the Ds-CNN method that uses frequency domain downsampling and convolutional neural network (CNN) to enhance the robustness of diagnosis of bearing faults by reducing the inter-sample variance and noise interference in the frequency domain through data augmentation. In addition, Guo et al. [15] proposed ACNN-BiLSTM (combining attention CNN and BiLSTM techniques), which is able to automatically select key features suitable for the current situation, which significantly improves the diagnostic accuracy in high-noise environments.

Although these deep learning methods show some advantages under strong noise background, they still have limitations. For example, Ds-CNN focuses on frequency domain feature extraction and noise reduction, which is not adaptable enough to strong noise; although ACNN-BiLSTM can focus on key features, the diagnostic accuracy still decreases significantly when the noise is extremely strong. Therefore, there is an urgent need to explore bearing fault diagnosis methods with better noise immunity and adaptability to improve the diagnostic accuracy and stability under strong noise background [16]. In this context, the stochastic resonance (SR) effect has become a solution of great interest due to its unique noise immunity. SR was originally proposed by Benzi et al. [17] in 1981, and its core idea is to introduce an appropriate amount of noise into the input signal to enhance the system's response to weak signals through the dynamic interaction between the noise and the nonlinear system [18, 19]. This effect is particularly effective under strong noise backgrounds, so since its introduction, SR has been widely used in various fields such as mechanics, mathematics and physics, demonstrating significant noise reduction effects. Based on the principle of SR, array stochastic resonance (ASR) offers a novel approach to bearing fault diagnosis in high noise environments. ASR enhances signal strength and facilitates energy transfer through multiple mutually coupled nonlinear systems, thereby improving diagnostic accuracy and reliability. As a result, ASR is expected to significantly improve the performance of bearing fault diagnosis under strong noise background. Therefore, this paper presents a novel method for bearing fault diagnosis by integrating deep learning with array stochastic resonance. The method leverages the advantages of deep learning in feature extraction and the ability of ASR in signal enhancement, aiming to improve the diagnostic effect under strong noise environments. The specific research contributions are as follows.

1) A new multi-branch dilated residual convolution structure is presented, so as to better capture the details and global information in the input feature map.

2) Array stochastic resonance module is implemented to enhance the robustness of the model under noise conditions.

3) The significant effect of the suggested approach in improving the diagnostic accuracy and reliability is fully verified after fault diagnosis tasks and detailed comparison experiments on the dataset at different noise levels.

The rest of the paper is structured as follows: Section 2 introduces the theoretical background of deep learning and array stochastic resonance, Section 3 details the model's architecture and its constituent components, Section 4 evaluates the proposed methods through comparative experiments and visualization, and Section 5 gives the conclusions of this paper.

2. **Proposed Methodology.**

2.1. **ResNet-18 neural network model.**

ResNet-18 is a classical deep neural network model introduced by He et al. [20] in 2016, which effectively solves the problems related to gradient vanishing, gradient explosion, and performance degradation that usually occur with increasing network depth. ResNet-18 is composed of 17 convolutional layers and a fully connected layer. It includes eight residual blocks, each containing two 3 × 3 convolutional layers. The basic component of the ResNet-18 architecture is the residual building block. Due to the fact that this architecture can effectively alleviate the problem of performance degradation and accuracy reduction that occurs as the depth of the neural network increases, we chose to use residual neural networks for bearing fault diagnosis and classification in this study, which ultimately increased the accuracy of fault identification.

2.2. **Dilated convolution.**

For CNN, a larger receptive field can capture a broader range of image information, and then enhance the network's ability to extract complex and global features [21, 22]. In CNN, it is common to employ three main techniques to expand the sensory field: pooling operations, enlarging the convolutional kernel size, and using dilated convolution. However, pooling operations lead to resolution degradation. The increasing of convolution kernel unavoidably results that the amount of calculation increases sharply. Hence, dilated convolution undoubtedly offers the optimal solution for expanding the receptive field.

In contrast to standard convolution, dilated convolution incorporates a parameter to the convolution kernel called the dilation rate. The dilation rate sets the amount of space between the elements in the convolution kernel. Specifically, when the dilation rate is 1, it is a conventional convolution. When the dilation rate is greater than 1, it indicates that a few pixels are skipped at intervals inside the convolution kernel for convolution. For a dilated convolution with convolution kernel size k and dilation rate r, the receptive field can be calculated using the formula: $r \times (k-1)+1$. It is obvious that dilated convolution is a sparse sampling method, which will lose the continuity of information and lead to grid effect. To mitigate this problem, a multi-branch dilated residual block is proposed to minimize the impact and improve network performance.

2.3. **Array stochastic resonance.**

Stochastic resonance is a mechanism that exploits the interaction between a nonlinear system, noise, and an input signal to enhance the detection of weak signals by appropriate noise intensity. The input signal refers to the signal that enters the system through external input, which can be deterministic or random. Noise as a random disturbance that occurs during the operation of the system can have an unpredictable effect on the output of the system. A nonlinear system defined by a nonlinear relationship between inputs and outputs forms a key part of the model. When the input signal and noise are processed by this system, an output signal is produced.

Through the joint action of these three components, the energy of the signal to be detected is increased [23].

Based on the principle of stochastic resonance, array stochastic resonance can enhance the detection effect of weak signals by applying independent random noise to multiple nonlinear systems at the same time, and thus through the interaction between them [24]. The array stochastic resonance model is shown in Figure 1.

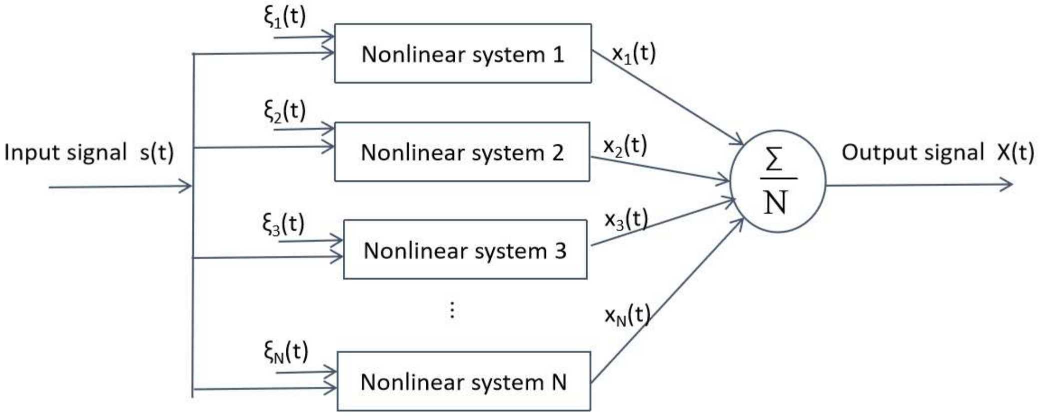


Figure 1. ASR model for nonlinear systems

In Figure 1, $s(t)$ represents the input signal, $\xi_i(t)$ $(i = 1, 2, \dots, N)$ denotes the noise for each array subsystem, $x_k(t)$ $(k = 1, 2, \dots, N)$ signifies the output of each subsystem, then $X(t)$ stands for the total output, and the formula is as follows:

$$X(t) = \frac{1}{N} \sum_{k=1}^{N} x_k(t) \tag{1}$$

The fault signals of some rolling bearings usually contain strong noise when they have been working under strong noise background for a long time and the working environment is relatively harsh. Array stochastic resonance can minimize the interference of noise on fault signals, and thus extract these signals efficiently in noisy background. Therefore, in this paper, the array stochastic resonance effect is integrated into the model.

3. The Proposed Method.

3.1. Improving ResNet18 neural network model.

To enhance ResNet18 neural network's efficiency in diagnosing bearing faults, this paper develops a model based on an optimized ResNet18 architecture. Initially, we substitute each convolution layer in layer1 with a multi-branch dilated convolution structure to extend the perceptual field, enabling the network to more effectively capture essential features within the input image. Secondly, we replaced the ReLU activation function in layer2 with multiple nonlinear systems and introduced noise to achieve the effect of array stochastic resonance, which can help the network in more accurately modeling the nonlinear relationships within the data, thereby enhancing its capability to diagnose bearing faults even in the presence of significant noise. Through the above improvement, we get a new network structure, which has stronger characterization and discrimination ability in the task of bearing fault diagnosis. The enhanced network architecture is shown in Figure 2.

3.2. Multi-branch dilated convolution structure.

In this paper, the multi-branch dilated convolution structure is designed as three branches, and an inflated convolution with

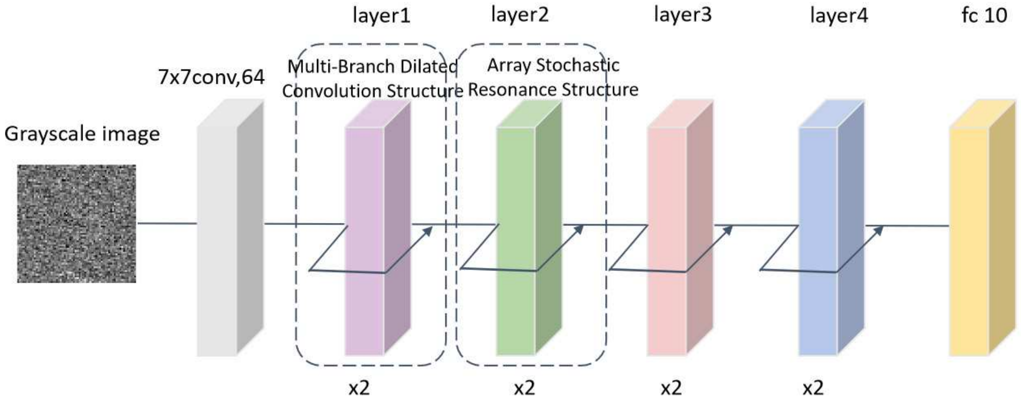


FIGURE 2. Improved ResNet-18 neural network structure

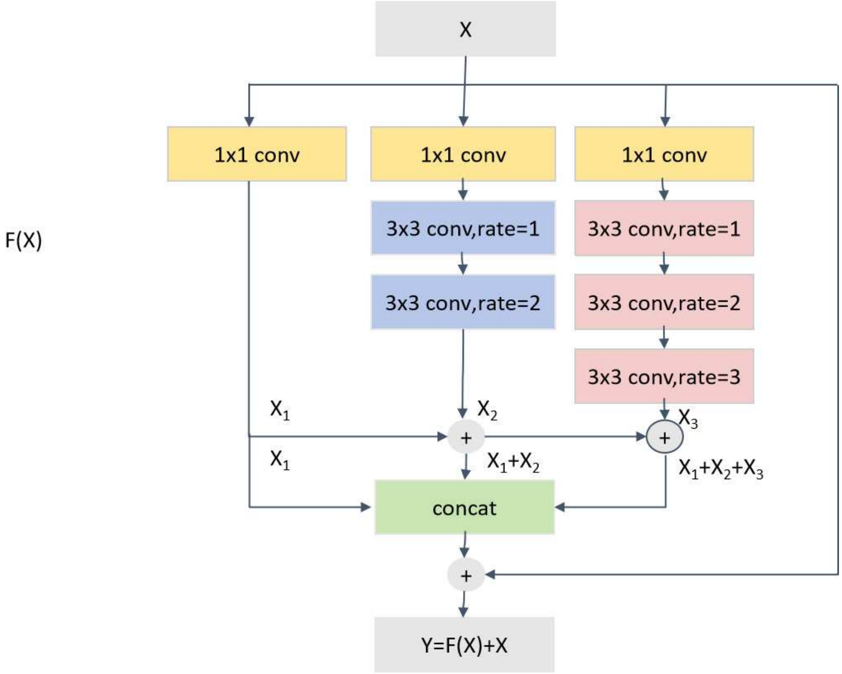


FIGURE 3. Multi-branch dilated convolution structure

convolution kernel size 3×3, expansion rates $r = 1$, $r = 2$ and $r = 2$ is used, which produces receptive fields with sizes 3×3, 5×5 and 7×7. In addition, dilated convolution does not sample the dilated regions, leading to discontinuous information extraction by the model. To mitigate this gap effect, the present study introduces a multi-branch dilated convolution structure, as shown in Figure 3.

Given X as the input feature, and Y as the output feature. The initial step for all three branches involves using standard convolutions with a 1×1 kernel to reduce the number of channels. Branch 1 remains the same, while branch 2 incorporates dilated convolutions with dilation rates of 1 and 2. Branch 3 includes dilated convolutions with dilation rates of 1, 2, and 3. Before combining the channels, the features extracted by each branch are as follows:

$X_1 = X * C_{1\times1}$
$X_2 = X * C_{1\times1} * D_{r=1} * D_{r=2}$
$X_3 = X * C_{1\times1} * D_{r=1} * D_{r=2} * D_{r=3}$

Among them, X_1, X_2 and X_3 represent the features derived from the respective branches; $*$ is a convolution operation; $C_{1\times 1}$ is an ordinary convolution with a convolution kernel of 1×1, where $D_{r=1}$, $D_{r=2}$ and $D_{r=3}$ are dilated convolution kernels of 3×3 with dilatation rates of 1, 2 and 3, respectively.

In this paper, the fusion mode $Y = \{X_1, X_1 + X_2, X_1 + X_2 + X_3\}$ of step by step superposition is added before channel concatenation, this means that the features extracted by branches 1, 2, and 3 are fused and then the combined features are merged with the original input data using an additive operation to generate the output. This design provides significant advantages in multi-scale feature extraction and feature fusion. By extracting features with different dilation rates (1, 2, and 3) in parallel, the network is able to effectively capture both local and global information of the signal, thus enhancing performance under strong noise background and better distinguishing between noisy and valid signals. Additionally, the step by step superposition fusion strategy ensures effective combination of features and information retention, further improving the accuracy of feature extraction and the robustness of diagnosis. Ultimately, the network is able to perceive signals more comprehensively under strong noise background, effectively improving the accuracy and reliability of bearing fault diagnosis.

3.3. **Array stochastic resonance structure.** Activation functions are a key component in neural networks used to introduce nonlinear properties in neurons, enabling the network to learn and process complex data and patterns more effectively. To enhance the neural network's performance, we have made some improvements to layer2, as shown in Figure 4.

After obtaining the residual outputs, we propose a novel approach using N three-stage dead-zone nonlinear systems (TDNS) instead of the conventional ReLU activation

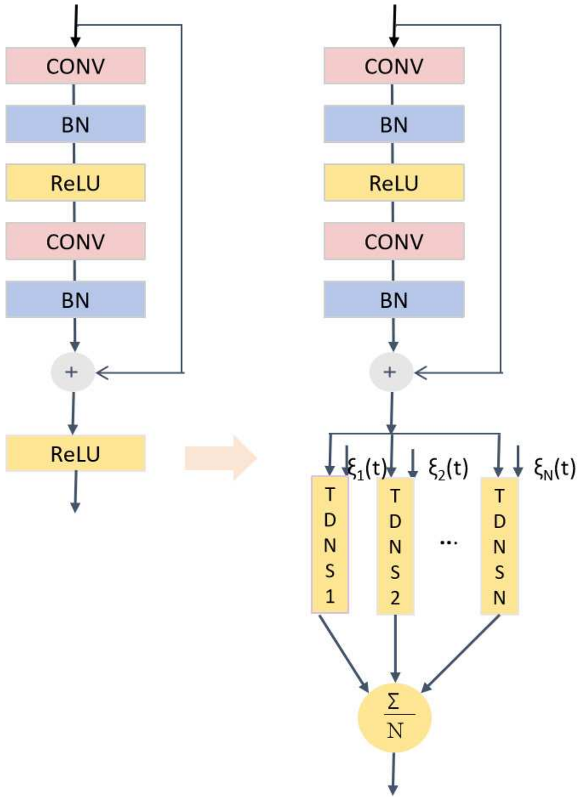


FIGURE 4. The ReLU activation function is replaced with N three-stage dead-zone nonlinear systems (TDNS)

function. The array stochastic resonance effect is generated by introducing noise into the input signal and passing it to the N dead-zone nonlinear system [25]. A three-stage dead-zone nonlinear system is formulated as follows:

$$D\left(u_k\right)=\left\{\begin{array}{ll} s_r(u_k-b_r), & u_k>b_r>0 \\ 0, & b_l\leq u_k\leq b_r \\ s_l(u_k-b_l), & u_k<b_l<0 \end{array}\right. \tag{2}$$

where, b_l, b_r, s_r, and s_l are dead-zone parameters, all of which are greater than 0. To simplify the complexity of parameter adjustment, assume that $|b_l|=|b_r|=b$, $|s_l|=|s_r|=s$, s and b are unknown constants, and these parameters are used to control the shape and characteristics of the activation function.

The introduction of this activation function can effectively prevent the gradient disappearance problem and enhance the modeling ability of complex features. Stochastic resonance is a phenomenon that introduces randomness, which helps the network better explore potential feature spaces during training. Compared to a single nonlinear system, array stochastic resonance using an array of multiple nonlinear systems can provide more accurate and robust signal feature extraction capabilities, and can adapt to a wider range of signal types and noise levels. Through the above improvements, we significantly enhance the performance of neural networks in bearing fault diagnosis, increasing the accuracy of feature extraction and fault classification, and effectively identifying bearing faults. Array stochastic resonance strengthens the signal through multi-system collaboration, effectively improving diagnostic accuracy in situations with weak signals and strong noise. This approach addresses the shortcomings of deep learning methods in the presence of strong noise interference, significantly enhancing the system's noise immunity and the reliability of fault feature extraction.

4. **Experiments and Analyses.**

4.1. **Dataset.**

The Case Western Reserve University (CWRU) bearing dataset was used for the experiments. The dataset was collected and compiled from CWRU's bearing test bed and contains vibration signal data under a wide range of operating conditions, which were collected by setting different loads (0 to 3 hp) and rotational speeds (1720 to 1797 revolutions per minute) to simulate the operation of bearings in a real industrial situations. The data we used was recorded at a sampling frequency of 12 kHz, and the dataset covers the following four main operating conditions (states): Normal (NORMAL), Inner Race Failure (IR), Outer Race Failure (OR), and Steel Ball Failure (B). Each failure condition contains three different damage diameters of 0.007, 0.014 and 0.021 inches. A total of ten states are included, including one normal state and nine fault states. The dataset are shown in Table 1.

4.2. **Dataset preprocessing.**

To assess the model's capability to recognize noisy data, we introduce several levels of Gaussian white noise to the original signals, simulating the presence of industrial noise. The signal-to-noise ratio (SNR) quantifies the relative strength of the signal compared to the noise. An SNR less than 0 indicates that the noise's impact energy exceeds that of the signal produced by the bearing. Conversely, an SNR greater than 0 signifies that the noise's impact energy is lower than that of the signal. Consequently, a lower SNR corresponds to more background noise and more intricate raw vibration data, making it more challenging to identify the faulty bearing [26, 27]. The formula is as follows.

$$SNR=10\log_{10}\frac{P_{signal}}{P_{noise}} \tag{3}$$

where P_{signal} signifies the average power of the signal, and P_{noise} represents the average power of the noise. In the experiments, white Gaussian noise with an SNR of -10 dB to -4 dB was introduced into the original time-domain signal to emulate a strong noise background.

Table 1. Ten fault states of bearing failure

Category	States	Conditions	Damage size	Label
0	NORMAL	Normal	None	NORMAL
1	IR	Inner Race Failure	0.007	IR_0.007
2	IR	Inner Race Failure	0.014	IR_0.007
3	IR	Inner Race Failure	0.021	IR_0.007
4	OR	Outer Race Failure	0.007	OR_0.007
5	OR	Outer Race Failure	0.014	OR_0.007
6	OR	Outer Race Failure	0.021	OR_0.007
7	B	Ball Failure	0.007	B_0.007
8	B	Ball Failure	0.014	B_0.007
9	B	Ball Failure	0.021	B_0.007

This study aims to improve the accuracy and efficiency of bearing fault diagnosis under strong noise conditions. For the purpose of extracting more rich feature information and visualizing failure modes, we convert the original one-dimensional fault signal of noisy bearing into two-dimensional gray image [28]. In order to generate a two-dimensional gray image with the size of $R \times R$ pixels, we extract a signal segment of length R^2 from the original time-domain signal. Subsequently, each pixel's intensity is computed using the formula:

$$P(i,r) = round\left(\frac{L(i \cdot R + r) - MinL}{MaxL - MinL} \times 255\right) \tag{4}$$

where $P(i,r)$ ($i = 1, 2, \ldots, R$; $r = 1, 2, \ldots, R$) denotes the pixel value in the resulting image, and $L(j)$ ($j = 1, 2, \ldots, R^2$) represents the signal value in the corresponding segment. The purpose of this formula is to map the intensity value of each pixel to between 0 and 255 to get a grayscale image. In this way, we can integrate information of the original signal into one image as shown in Figure 5, and use the image processing algorithm for feature extraction, classification and other operations.

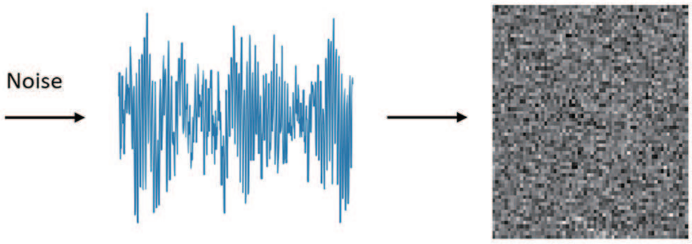


Figure 5. Data preprocessing procedure

4.3. **Experimental setup.** The software environment includes the PyCharm integrated development environment (IDE) and the programming language is Python 3.8, using the PyTorch deep learning framework. The experimental platform consists of a computer equipped with an NVIDIA GeForce RTX 2080 Ti GPU. During network training, the epoch of the network is set to 130, batchsize to 256, the learning rate is the StepLR with a raw learning rate of 0.001. Additionally, the optimization algorithm used is Adam. The settings of relevant parameters are determined by referring to existing literature and combined with experimental tuning, aiming to ensure that the system can achieve effective fault diagnosis under noisy background. In the case of an SNR of -7 dB, the dead-zone threshold parameter $b = 0.7$ and the sensitivity parameter $s = 1$ are chosen, and the Gaussian white noise with a standard deviation of 0.3 is introduced as the interference. The whole system consists of 10 nonlinear systems to enhance the signal detection capability by generating the array stochastic resonance effect. To further optimize the detection effect, the standard deviation of the noise and the number of nonlinear systems are appropriately adjusted for the datasets with different SNR in the experiments.

4.4. **Comparison and analysis.** To verify the superiority of the network model in diagnosis of bearing faults, we tested it against various models under strong noise background conditions. Table 2 lists the performance accuracies of these models at different SNR.

TABLE 2. Classification accuracy of different SNR on the CWRU dataset (%)

Model	−10	−9	−8	−7	−6	−5	−4
Our model	81.13	88.33	93.53	97.85	98.70	99.95	99.98
WDCNN2d [29]	63.38	75.43	84.48	92.28	96.05	99.10	99.38
CNN2d [30]	56.08	65.75	78.70	85.78	95.50	98.48	98.53
BiLSTM2d [30]	49.58	61.15	70.30	81.65	89.50	95.80	96.68
IFD-MDCN [16]	81.77	–	89.25	–	93.67	–	–
MDFN+SE [31]	–	–	–	–	93.26	–	99.07
MSCNN-BiLSTM [32]	–	–	–	–	90	–	–

As can be seen from Table 2, the model proposed in this paper still maintains high accuracy under strong noise background. The performance of the model is relatively stable under various SNR conditions, especially when the SNR is -7 dB, the accuracy reaches 97.85%. This result indicates that the model has significant noise immunity and is able to effectively identify faulty signals and maintain good performance even under extreme noise conditions. In addition, the accuracy of the model in this paper shows a steady increase with the improvement of SNR. In contrast, the performance of other comparison models such as WDCNN2d, CNN2d and BiLSTM2d is relatively weak, and their accuracies are significantly lower than that of our method under low SNR conditions. This further validates the effectiveness of the proposed model under strong noise background and provides strong support for fault diagnosis in practical applications.

In order to evaluate the superiority of the proposed model more comprehensively, Figure 6 shows the radar chart comparing the performance of different diagnostic methods at SNR $= -7$ dB. The radar plot contains four key performance metrics: accuracy, recall, precision, and F1-score. It can be seen that the model proposed in this paper outperforms the other comparative models in all metrics, especially in accuracy and F1-score. This fully reflects the significant advantages of our model and verifies its effectiveness and reliability in practical applications.

The confusion matrix in Figure 7 reflects the recognition results when SNR is -7 dB. As observed, the model shows excellent performance in NORMAL, IR and OR fault categories. Misidentified label data is concentrated in the ball class, this is because they have similar signal distributions, making them difficult to distinguish. Table 3 presents the evaluation results of the metrics for each class. It is evident from the table that the

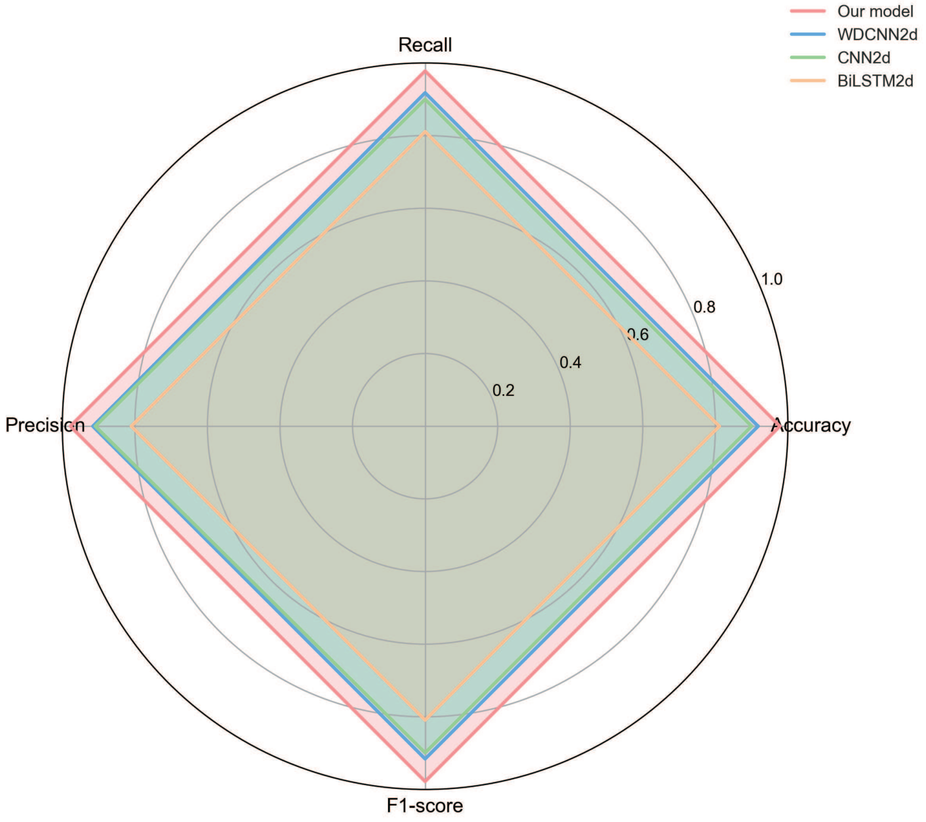
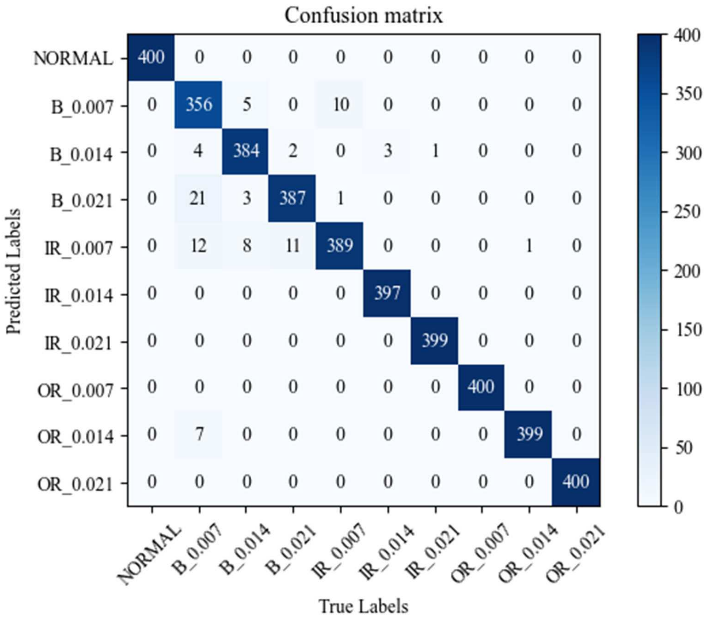


Figure 6. (color online) Radar chart of performance comparison of different models at SNR = -7 dB



	NORMAL	B_0.007	B_0.014	B_0.021	IR_0.007	IR_0.014	IR_0.021	OR_0.007	OR_0.014	OR_0.021
NORMAL	400	0	0	0	0	0	0	0	0	0
B_0.007	0	356	5	0	10	0	0	0	0	0
B_0.014	0	4	384	2	0	3	1	0	0	0
B_0.021	0	21	3	387	1	0	0	0	0	0
IR_0.007	0	12	8	11	389	0	0	0	1	0
IR_0.014	0	0	0	0	0	397	0	0	0	0
IR_0.021	0	0	0	0	0	0	399	0	0	0
OR_0.007	0	0	0	0	0	0	0	400	0	0
OR_0.014	0	7	0	0	0	0	0	0	399	0
OR_0.021	0	0	0	0	0	0	0	0	0	400

Figure 7. Confusion matrix when SNR is -7 dB

model performs very well in Normal and outer classes, demonstrating high classification accuracy. The ball type bearing with different diameters performed better overall, but the recall value was slightly lower, probably due to the higher miss rate. Among them, ball_36 performs better than ball_18 and ball_54 in all indicators. The inner type bearings perform

TABLE 3. The evaluation results of the indicators when SNR is -7

	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)
normal	100	100	100	100
ball_18	98.5	96	89	99.6
ball_36	99.4	97.5	97	99.7
ball_54	99	93.9	96.8	99.3
inner_18	98.9	92.4	97.2	99.1
inner_36	99.9	100	99.2	100
inner_54	100	100	99.8	100
outer_18	100	100	100	100
outer_36	99.8	98.3	99.8	99.8
outer_54	100	100	100	100

TABLE 4. Results of ablation experiments

Model	Accuracy (%)
ResNet-18	97.03
ResNet-18+MBDC	97.33
ResNet-18+MBDC+ASR (Our model)	97.85

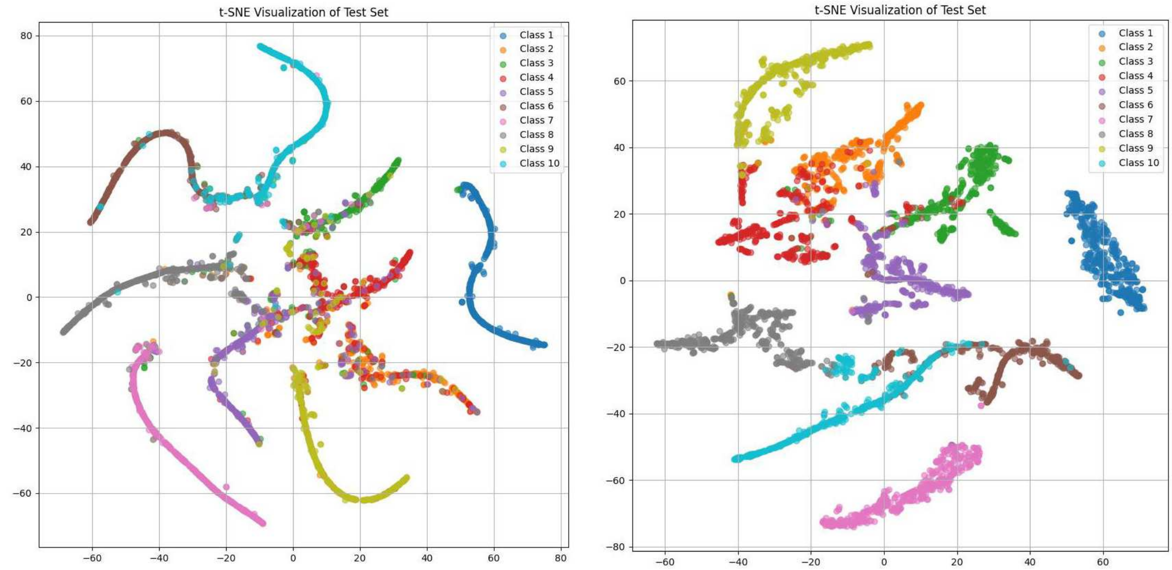
very well in precision, recall and specificity at different diameters, especially inner_36 and inner_54. On the whole, the fault bearing of different types and diameters is different in the identification of the model, but the model performs best in the identification of inner and outer ring faults. For types of ball bearing, the performance of the model slightly down, needs to be further optimized to reduce the non-response rates.

To confirm the effectiveness of the proposed ResNet-18 network enhancement method, when SNR is -7 dB, the results of the ablation experiment were performed by setting different conditions, as shown in Table 4. It is evident that the network enhancement method introduced in this study can effectively diagnosis bearing faults in strong noise background.

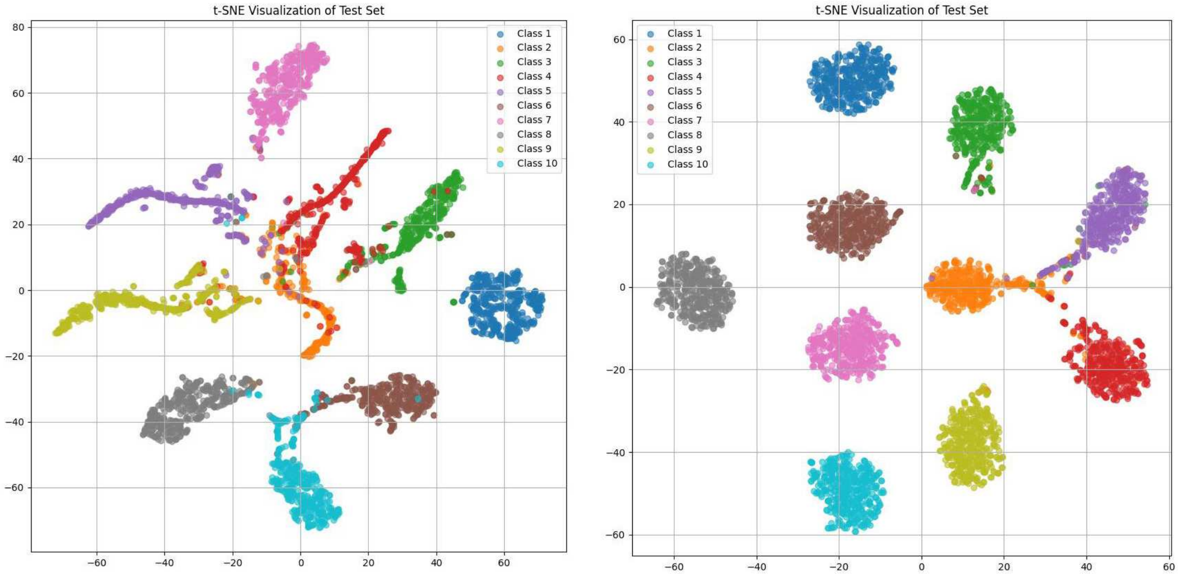
In conclusion, the model proposed here can effectively suppress the influence of noise on bearing fault diagnosis. By introducing multi-branch dilated convolution and stochastic resonance techniques, the model is engineered to both extract valuable features from the signal and minimize noise interference. This makes the model perform well in strong noise backgrounds with higher accuracy and more reliable bearing fault diagnosis. At the same time, it should be noted that when the SNR reaches -10 dB, the accuracy of almost all models drops to a very low level, which also indicates that there are still great challenges for image recognition tasks under strong noise background.

4.5. **Data visualization.** To evaluate the method proposed in this study, t-SNE was used to visualize the mapping of the high-dimensional feature data extracted from the last layer of each model into the low-dimensional space with an SNR of -7. As shown in Figure 8, different colored dots represent different categories.

The results of the CNN and BiLSTM methods show that samples of the same category are mixed in different regions and cannot be correctly divided into corresponding regions. WDCNN method performs better than the first two and is able to distinguish between categories well, but there are still misclassification results. However, the method proposed in this paper shows better results in the visualization results. The samples of each category are correctly divided into the corresponding regions, and the clustering effect is obvious.



(a) BiLSTM2d (b) CNN2d



(c) WDCNN2d (d) Network model in this paper

FIGURE 8. (color online) Visualization results of different models: (a) BiLSTM2d, (b) CNN2d, (c) WDCNN2d, and (d) network model in this paper when the SNR is -7. The two dimensions of the t-SNE plot represent the similarity of the high-dimensional data in the low-dimensional space, with the horizontal and vertical coordinates reflecting the position of the data in the two main directions of variation, respectively.

It is demonstrated by these results that our method has better classification and feature extraction capabilities in the bearing fault diagnosis task.

5. **Conclusions.** A new method for bearing fault diagnosis based on deep learning and array stochastic resonance is proposed in this paper to solve the problem of low-accuracy bearing fault diagnosis under strong noise background. We constructed a bearing fault diagnosis model on the basis of residual network by using multi-branch structure dilated

convolution and adding array stochastic resonance module. The performance of different models under various SNR is evaluated using publicly available dataset from CWRU. In the strong noise background, the traditional deep learning models (such as WDCNN, BiLSTM, and CNN) show certain accuracy in bearing fault diagnosis, but they are greatly affected by the noise interference, which leads to large fluctuations in performance. In contrast, the model suggested in this study shows better adaptability and robustness under strong noise background, which can effectively suppress noise interference and improve diagnostic accuracy and reliability. This approach based on deep learning and array stochastic resonance shows potential engineering applications. However, the model still has some limitations. The training time increases by approximately 10 seconds with each round, which may affect the overall training efficiency. In addition, adjusting the parameters of the nonlinear system adds complexity to the usage process. Future research could reduce the training time by optimizing the model structure or using more efficient training algorithms. Furthermore, exploring adaptive stochastic resonance techniques to dynamically adjust system parameters is expected to significantly improve the efficiency and accuracy of fault diagnosis.

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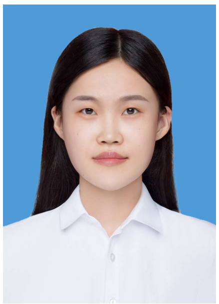
Author Biography



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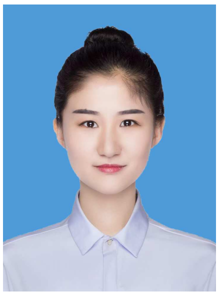

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