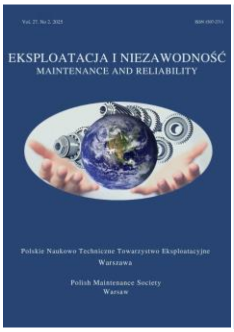

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Fault diagnosis method of automobile rolling bearing based on transfer learning and improved DenseNet

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Highlights

- The conversion of vibration data into image data improves diagnostic accuracy.
- Sub domain adaptation improves the diagnostic ability for cross condition data.
- Attention mechanism improves diagnostic efficiency and reduces diagnostic time.

Abstract

Aiming at the problems caused by ignoring the time series characteristics, the scarcity of labeled data and the long diagnosis time in the fault diagnosis of one-dimensional vibration signals of automobile bearings, a new method combining improved DenseNet and transfer learning is proposed in this study. This method uses Recurrent Plot (RP) technology to convert one-dimensional vibration data into two-dimensional images to fully tap the potential value of time series. By optimizing the DenseNet network structure, the fault features are extracted effectively.Lightweight network design and MobileViT Attention mechanism are used to reduce the number of parameters and improve computing efficiency. With the help of transfer learning technology, the fault features in the source domain are transferred to the target domain, which solves the problem of cross-condition diagnosis and greatly reduces the diagnosis time. The experimental results show that the proposed method can improve the accuracy of fault identification and diagnosis efficiency, and achieve accurate classification.

Keywords

fault diagnosis, transfer learning, dense net, recurrence plot, mobileViT attention mechanism

1. Introduction

As the fundamental component of rotating machinery, the reliable operation of rolling bearings is paramount to industrial production **Błąd! Nie można odnaleźć źródła odwołania.**.With the advancement of intelligent manufacturing strategies in the automotive industry, bearing fault diagnosis has assumed an increasingly prominent role in preventing production accidents and enhancing equipment efficiency [2]. Bearing fault diagnosis not only enables early detection of potential faults, thereby saving maintenance costs and time, but also effectively mitigates substantial losses resulting from fault progression [3]. Nevertheless,the operating environment for vehicles and production equipment is intricate and variable, rendering bearings susceptible to damage. Consequently, bearing fault diagnosis stands as a critical factor in ensuring the robust and stable operation of automotive equipment while averting major accidents.

Conventional fault diagnosis methods such as principal component analysis [4], Fourier transform [5],variational mode decomposition [6], and wavelet transform [7] are often constrained by noise interference and the subjectivity of artificial feature extraction, leading to diagnostic results that are vulnerable to human factors and involve cumbersome processes. Moreover, these traditional methods heavily rely on expert experience and require a high dependence on professional technical personnel,

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making it challenging to meet the efficiency and accuracy requirements of modern bearing fault diagnosis.

With the rapid advancement of artificial intelligence technology, bearing fault diagnosis based on deep learning has emerged, successfully transcending the limitations of traditional methods [8]. Deep learning algorithms such as artificial neural networks [9], convolutional neural networks [10], autoencoders [11], and long short-term memory networks [12] can autonomously learn and extract profound fault features from extensive vibration data, thereby significantly reducing reliance on manual feature extraction and expert knowledge. This enhances the objectivity, accuracy, and efficiency of the fault diagnosis process. Furthermore, deep learning exhibits robust generalization capabilities that enable it to adapt to various working conditions and environments for bearing fault diagnosis, thus enhancing diagnostic reliability and practicality.

The application of deep learning in bearing fault diagnosis also faces some challenges. In real industrial applications, it is difficult to obtain fault marker samples under all working conditions due to the difference in gearbox speed, load and monitoring position, which may lead to significant distribution difference in the feature space of training and test data collected by sensors. Transfer learning, as a major leap forward in the field of artificial intelligence in recent years, aims to use existing knowledge and experience to overcome challenges in related but not completely consistent fields [13]. This approach makes full use of previously accumulated wisdom, enabling machines to quickly adapt and efficiently solve problems in different but related fields, thus driving the continuous development and innovation of artificial intelligence technology.

Transfer learning [14] is a technical means with great potential and prospect, which can effectively transfer the learning results accumulated by the model in the source domain to the new target domain tasks, so as to realize the effective transfer and application of knowledge. Wang Jian et al. [15] combined transfer learning and attention mechanism to build WDDANN model for fault classification of rolling bearings under varying working conditions, improve classification efficiency, achieve accurate fault diagnosis, and verify its advantages. Wang Keding et al. [16] aimed at the scarcity of negative samples for fault diagnosis of mine fan bearings, the new method used deep transfer learning to solve the problem. The CNN-BiGRU-RF model was constructed to extract the deep fault characteristics.The parameters of transfer learning are fine-tuned, and the identification accuracy is high and the diagnosis effect is excellent. Gong Xiaoyun et al. [17] proposed a multi-head convolutional neural network transfer learning model to realize multi-source diagnosis in view of single-source signal limitation and small-sample compound faults. Large sample migration optimizes small samples,improves recognition accuracy and shortens convergence time.

To solve these problems, this paper proposes a method that combines RP recursion graph with improved Densenet network. Methods Make full use of the time series information of vibration signals, and explore the potential value of time series of vibration data by converting one-dimensional data to two-dimensional data through RP recursion graph, so that the deep network structure can effectively extract fault features. By optimizing the network structure and adding the MobileViTAttention mechanism, a lightweight parameter network is realized, which greatly reduces the need for parameter adjustment and improves the computing efficiency. Combined with the subdomain adaptive method of transfer learning technology, the accuracy of fault identification is improved, and the time of fault diagnosis is greatly shortened. This paper also combines the subdomain adaptive method of transfer learning technology. This allows the model to more accurately capture differences in data distribution between different subdomains, such as different operating conditions, equipment types, or operating environments. By adaptively adjusting the model parameters to match the characteristics of each subdomain, the method greatly enhances the generalization ability and robustness of the model, making it more flexible to deal with complex and changeable diagnostic tasks.

2. Basic theory

2.1. Recurrence Plot

Recurrence Plot is a method for the analysis of time series data that reveals features such as structure, periodicity and mutation within the data by showing patterns of the time series reproducing or nearly reproducing its past state at different points in time.

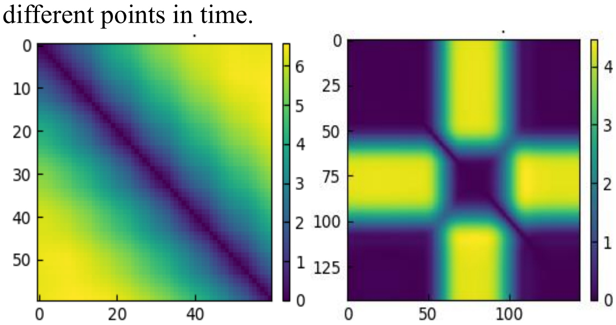


Fig.1. Recurrence Plot.

The core idea of recursive graphs is based on phase space reconstruction, which converts time series data into trajectories in phase space and analyzes the reproducibility of these trajectories. By observing whether the states of the system are similar at different time points, the repeatability or periodicity of the system behavior can be analyzed. Recursion graphs perform well in the analysis of short time series data. They can test the stationarity and intrinsic similarity of time series and provide important prior knowledge about similarity, information and predictability.

2.2. Preadaptation

Domain adaptive [18] is an important concept in machine learning and transfer learning, which aims to solve the problem of degraded model performance caused by the difference in data distribution between different domains. By learning and adjusting the differences between the source domain and the target domain, the model of the source domain can be migrated to the target domain and maintain good performance on the target domain.

2.2.1. Sample adaptive

Sample self-adaptation is a strategy that makes the distribution of samples in the source domain and the target domain basically the same by resampling the samples in the source domain. The core goal of this method is to make the distribution of source domain and target domain as close as possible, and then retrain the classifier on the sample set after resampling, so as to achieve more accurate target domain classification effect and improve the performance of the model in the target domain. Sample adaptation is often used in practical applications to deal with problems such as data imbalance or noisy data.

2.2.2. Feature adaptive

Feature adaptation is to map the features of the source domain and the target domain to a common feature subspace by learning the common feature representation, so that the distribution of the source domain and the target domain can be consistent as much as possible in this common feature space. This method usually uses some feature transformation techniques, such as maximum mean difference (MMD) method, principal component analysis (PCA) or Autoencoder (Autoencoder), to extract the most recognizable features and eliminate the impact of domain differences on model performance.

2.2.3. Model adaptive

Model adaptation is a method of self-adaptation at the model level.The basic idea of this method is to directly modify the model structure or parameters of the source domain to fit the data distribution of the target domain. Model adaptation usually involves modifying the error function of the source domain to take into account the error of the target domain, so as to optimize the performance of the model on the target domain. This approach is especially effective when the source domain and the target domain are quite different.

2.3. Subdomain adaptive

Subdomain adaptation is an important branch of domain adaptation [19],which focuses on performance improvement on specific subdomains (or subtasks, subcategories). While traditional domain-adaptive approaches typically focus on differences in data distribution across domains or tasks, subdomain-adaptive goes a step further by attempting to align and fit within more fine-grained subdomains.

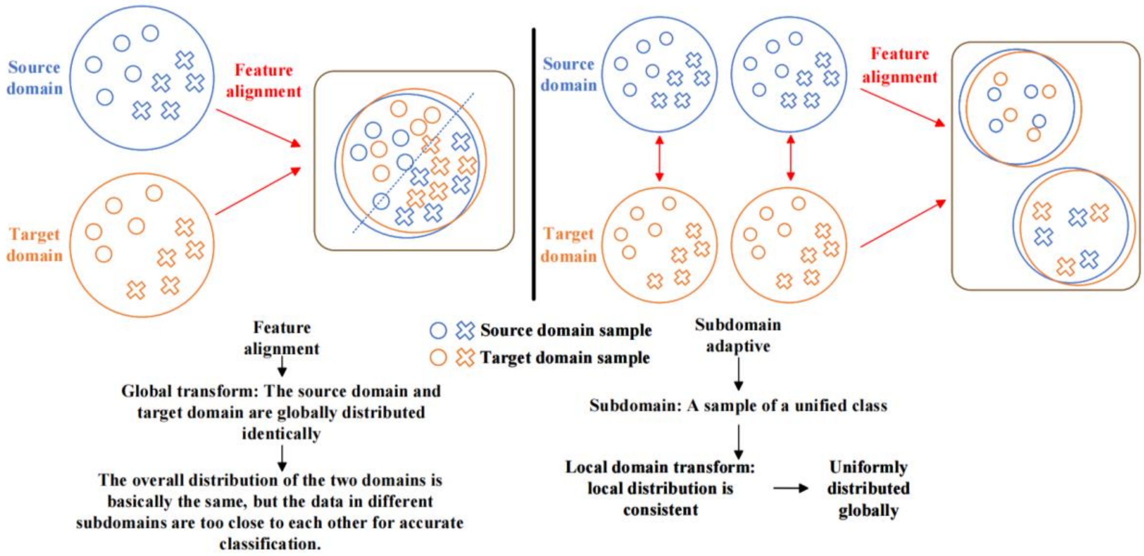


Fig.2. Sub-domain adaptive.

In subdomain adaptive, data from the source domain and target domain are divided into different subdomains based on some conditions or labels. These conditions can be class-based, task-based, or based on other specific attributes or characteristics. By dividing the subdomains, the differences in data distribution between different subdomains can be more accurately captured. Subdomain adaptive methods perform specific adaptation and alignment operations for each subdomain. This can include adjusting model parameters, modifying feature representations, or applying specific adaptation algorithms. The goal is to make the data distribution of the source domain and the target domain as close as possible within each subdomain, thereby improving the performance of the model on the target subdomain.

Subdomain adaptation is widely used in practical applications. For example, in the task of fault diagnosis and analysis of rolling bearings in different working conditions, the data may be different between different working conditions, and subdomain adaptive can help the model better adapt to the data form in different working conditions.

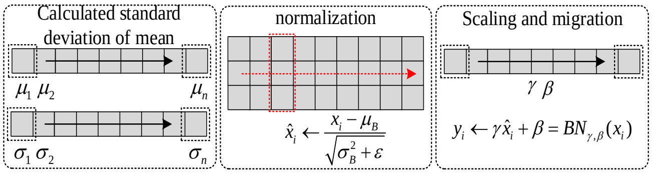


Fig.4. BatchNormalize1d schematic.

2.4. Densenet

DenseNet is a residual-connected network (ResNet) based improvement proposed by Hongyuan Li, Heng Huang, and Zhihua Zhang in 2017. DenseNet was initially applied to visual fields such as image classification scenarios. Thanks to network structure optimization, its performance and efficiency have been widely praised. The dense connection module in the model has also been applied to many other scenarios.

2.4.1. Dense connected block

DenseBlock [20], a dense connection module, as the core of DenseNet, realizes the close connection of the output of each layer and overcomes the problems of layer selective discarding and information blocking in ResNet. Dense connections ensure gradient cross-layer propagation, stabilize deep network training, promote efficient reuse of features, and improve parameter efficiency and information transfer efficiency. DenseBlock reduces the number of parameters through parameter sharing and reuse, combined with the number of small convolution cores and filters, and improves the running speed of the network.

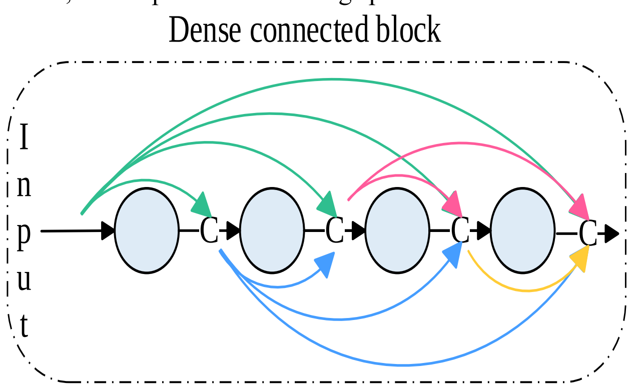


Fig.3. DenseBlock.

(1) Batch normalized layers

In the field of deep learning, BN layer is a widely used technology. Its core function is to reduce the variation of the input distribution in the training process and promote the speed of model convergence by normalizing the input data of each batch. Specifically, the BN layer can adjust the input data to a distribution with a mean of 0 and a variance of 1 to optimize the training effect of the model. It can help alleviate the gradient problem and make network training more stable. BN layer introduces randomness, enhances network generalization ability, and improves test performance. At the same time, BN layer is used as a regularization method to limit the input of each layer, reduce the risk of overfitting, and improve the generalization ability. The calculation principle is simple and effective.

(2) LeakyReLU Activation layer

Compared to the ReLU function, the LeakyReLU function solves the problem of ReLU having a zero gradient in a negative region by assigning a tiny linear coefficient (e.g. 0.01x) to the negative input. This adjustment helps extend the scope of the ReLU function to cover the entire range of real numbers. The slope parameter λ is set to a value close to 0.01 so that the function extends from negative infinity to positive infinity.

$$Leak\,Re\,L\,U\big(Leak\,Re\,L\,U(z)\big) = \left.\begin{cases} z & ,z>0 \\ \alpha z & ,z\le 0,\ \ \alpha=0.1 \end{cases}\right\} \quad (1)$$

$$\delta^l = \left.\begin{cases} \delta^{l+1} & ,\ \ z^l>0 \\ \alpha\delta^{l+1} & ,\ \ z^l\le 0,\ \ \alpha=0.1 \end{cases}\right\} \quad (2)$$

The LeakyReLU activation function introduces a tiny positive slope on the negative half axis to deal with the possible "dead zone" problem in the ReLU activation function. This improvement allows LeakyReLU to maintain a certain response even when the input is negative, thus improving the flexibility and generalization ability of the model. The slope parameter λ is a hyperparameter that needs to be set manually and is usually set to 0.01. Because of this slope, LeakyReLU ensures that the neuron weights are updated during training, even if the input value is less than 0, thus avoiding a complete loss of information.

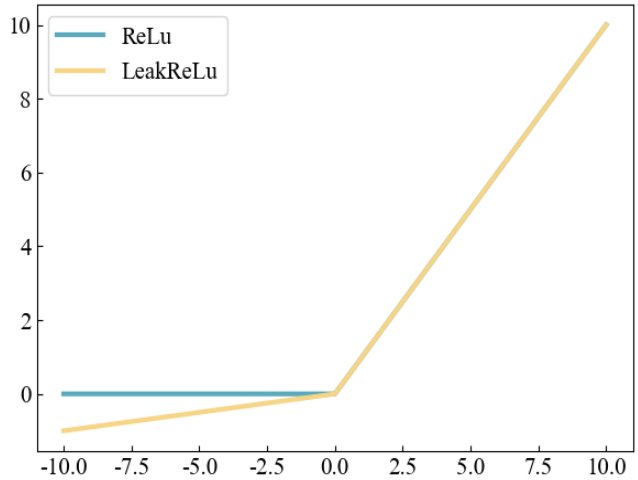


Fig.5. Image of the LeakyReLU function with a linear coefficient of 0.1.

2.4.2. Transition layer

Dense blocks increase the feature dimension, and DenseNet introduces a transition layer to control parameters and computational complexity. The transition layer includes 1x1 convolution and 1x2 averaging pooling to reduce the feature dimension and connect the dense layers. Although the 1x1 convolution seems to be a simple multiplication, it achieves nonlinear mapping after the activation layer, changes the number of channels, maintains the feature size, and deepens the network to learn complex features. Its advantages include channel dimension increase/reduction, addition of nonlinear features, cross-channel information interaction integration.

DenseNet consists of DenseBlock and Transition. In this paper, four layers of dense connected blocks are set up, each layer has 1, 2, 3, and each two Denseblocks are connected in series for Transition. The structure diagram is as follows:

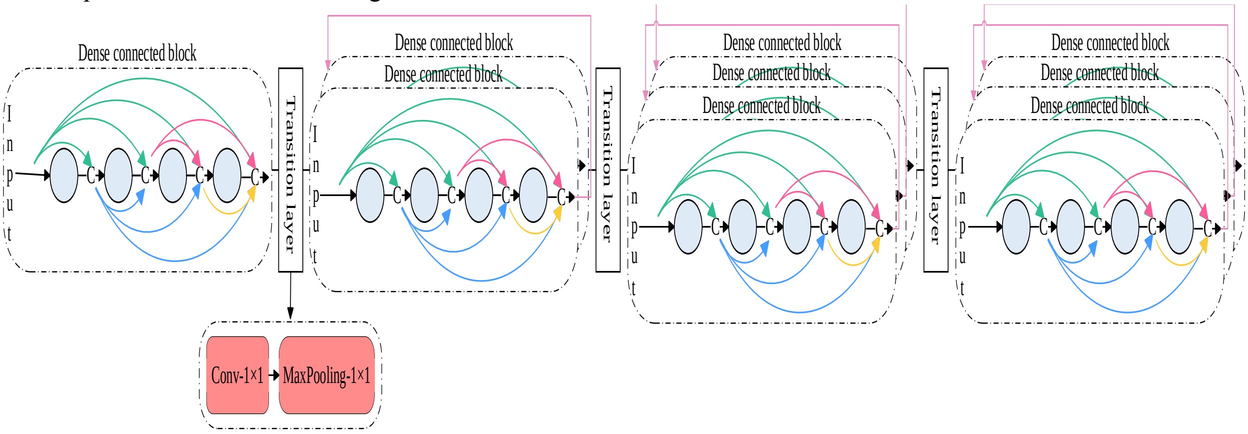


Fig.6. Dense connection block and transition layer structure diagram.

3. Improved DenseNet model

3.1. Attention mechanism

MobileViTAttention [21] is a visual attention model for mobile devices, which is designed based on the attention mechanism of Transformer. MobileViTAttention is designed to enable efficient image processing and vision tasks on mobile devices with limited computing and storage resources.

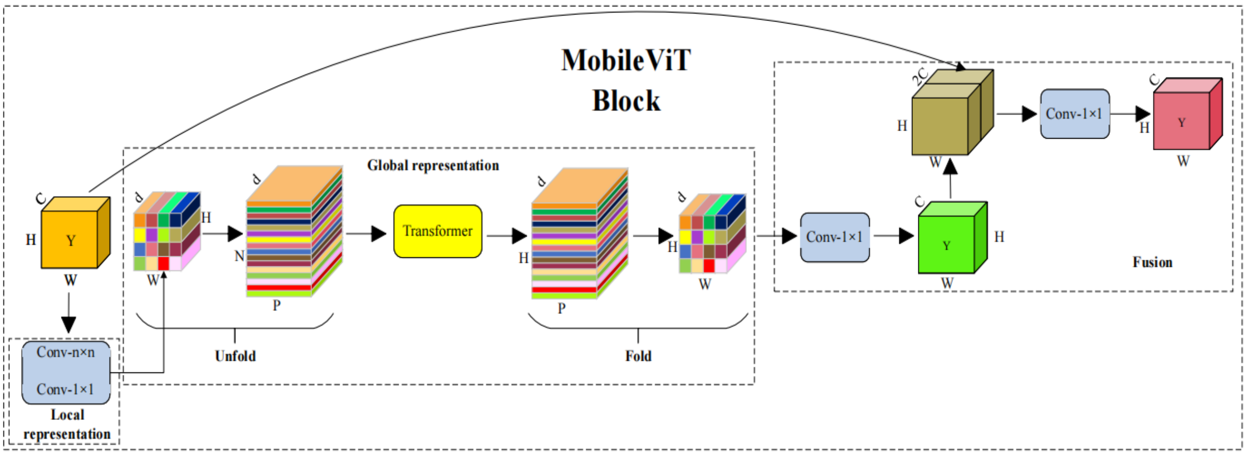


Fig.7. Structure diagram of the attention mechanism of MobileVit.

The core idea of MobileViTAttention is to split the input image into small blocks and use Transformer's attention mechanism to encode and aggregate these blocks. Compared to the traditional Transformer model, MobileViTAttention employs several optimization strategies to accommodate the resource constraints of mobile devices, it uses deep separable convolution to reduce the amount of computation, and uses a low-rank attention mechanism to reduce storage requirements.

MobileViTAttention is designed to enable efficient visual tasks such as image classification, object detection, and image segmentation on mobile devices. It significantly reduces the need for computing and storage resources while maintaining high accuracy, allowing mobile devices to better cope with complex visual tasks.

3.2. RP-Densenet Network parameters

Tab.1. RP-Densenet network parameters.

layer	Output size	Network layer
Recursion graph	28×28	
Convolution layer	28×28	7×7,s=2,p=3
Pooled horizon	28×28	1×1 max pooling, s=2, p=1
MV attention mechanism		

layer	Output size	Network layer
Dense block 1	28×28	$\begin{pmatrix}\text{Convolution}1\times1\\\text{Convolution}3\times3\end{pmatrix}$
Connecting layer 1	28×28 14×14	Convolution 1×1 Convolution2×2
Dense block 2	14×14	$\begin{pmatrix}\text{Convolution}1\times1\\\text{Convolution}3\times3\end{pmatrix}$
Connecting layer 2	14×14 7×7	Convolution 1×1 Convolution2×2
Dense block 3	7×7	$\begin{pmatrix}\text{Convolution}1\times1\\\text{Convolution}3\times3\end{pmatrix}$
Connecting layer 3	7×7 3×3	Convolution 1×1 Convolution2×2
Dense block 4	3×3	$\begin{pmatrix}\text{Convolution}1\times1\\\text{Convolution}3\times3\end{pmatrix}$
Classification level	3×3 global mean pooling fully connected layer, softmax	1×1

3.3. Migration network construction and process

In this paper, a model-based transfer learning method is adopted, the core of which is to share the weight parameter information of the source domain and the target domain model to realize the model transfer.

A new network architecture is constructed by using the pre-trained weights of the source domain and fine-tuning with a small number of target domain samples. The ability to extract non-robust features is improved, the model parameters that need to be trained are significantly reduced, the training time is shortened, and the deployment speed of the model is accelerated.

The construction of bearing fault diagnosis model follows the systematic and rigorous steps. The network model is trained with sufficient sample data and its parameters are determined to ensure that the model can fully learn the inherent laws and features of the data. The frozen part of the network layer is responsible for extracting the underlying features to preserve the valid information that has been learned. A new fully connected layer is added on top of the frozen layer, and the parameters of the new layer are optimized by fine-tuning a small number of target domain samples to make the model better adapt to the new task requirements. Through these steps, an efficient and suitable bearing fault diagnosis model is constructed, which not only uses the original domain knowledge, but also improves the performance through transfer learning, and provides a strong support for bearing fault diagnosis.

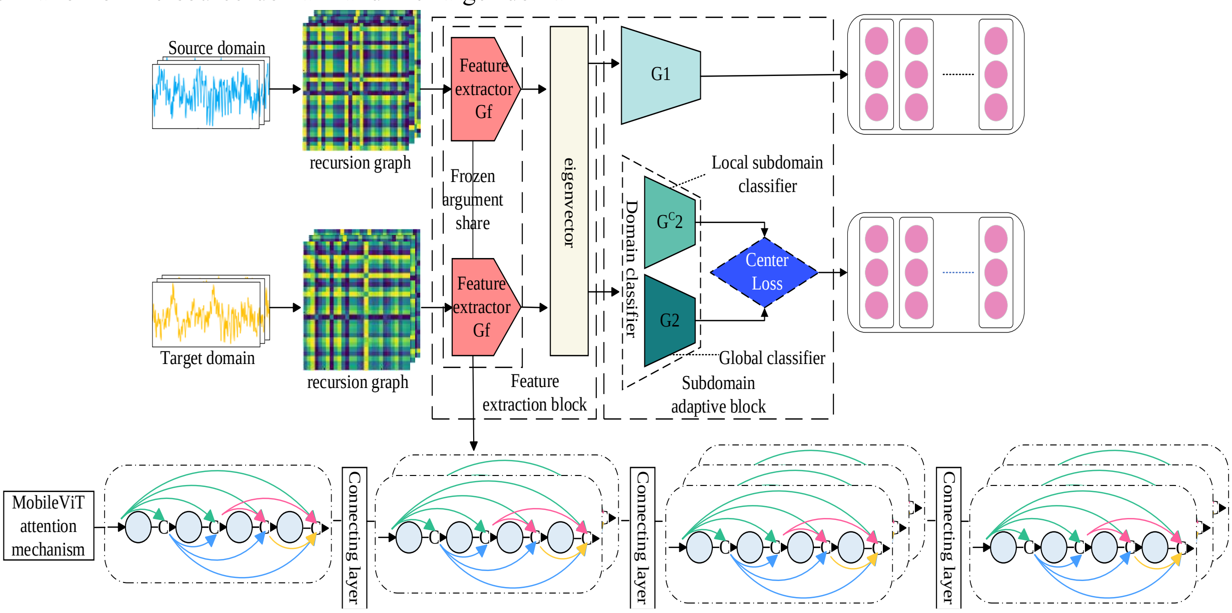


Fig.8. RP-DenseNet Transfer Network Flow Diagram.

The model method in this paper converts vibration signals into recursive graph images as input, and uses the improved Densenet as the fault diagnosis model to extract features from the input images. The flow chart of the proposed method is shown in the following figure.

(1) Conventional rolling bearing vibration signals are taken as source domain data, and after necessary pre-processing, these signals are converted into RP images, and then the corresponding data set is constructed.

(2) A fault diagnosis model based on Densenet is trained by using source domain data set to ensure that the model is fully trained and the trained source domain fault diagnosis model is obtained.

(3) Another part of the rolling bearing vibration signal is

selected as the target domain data, which is also preprocessed and converted into recursive graph images, and the corresponding target domain data set is constructed.

(4) Transfer the network architecture and weight parameters of the source domain fault diagnosis model to the target domain fault diagnosis model. According to the preset parameter updating strategy, part of the migrated parameter weights are retained and locked to ensure that these weights are not updated in the subsequent training.

(5) Use the training data set of the target domain to train the diagnosis model of the target domain, and fine-tune and update the remaining network parameters and weights. The aim is to optimize the diagnosis model of the target domain and improve its adaptability to the data of the target domain.

(6) After the training of the target domain diagnostic model is completed, the test data set is used to test the model, and the diagnostic performance of the model is evaluated by the final diagnostic accuracy rate.

4. Experiment

4.1. Data enhancement

Firstly, 1024 data points are extracted continuously from the original one-dimensional vibration data set of bearings. Then, these extracted data points are recursively mapped to generate a two-dimensional image with a size of 28×28. In order to enhance the diversity and generalization ability of these image data, the generated images were randomly flipped 40% horizontally and 60% vertically. In order to ensure the stability and convergence of model training, the image is normalized to make it have a uniform numerical range. After the above processing, these images are extended to the entire data set. This process helps to capture more feature information in the learning process of the model network. The whole data set was randomly divided into a training set and a test set at a ratio of 4:1 for the training and performance evaluation of the model.

4.2. Case Western Reserve University bearing failure dataset

The test used a bearing data set from Case Western Reserve University, which covers drive bearing test data sampling frequencies of 12kHz, 48kHz, and fan end bearing data sampling frequencies of 12kHz.

Experimental platform composition:

(1) A 2 HP electric motor;

(2) Torque sensor/decoder;

(3) a power tester;

(4) Controller.

This test is based on a test data set of a drive bearing with a sampling frequency of 12kHz. The dataset covers three different fault types: outer ring fault (OF), rolling fault (RF), and inner ring fault (IF). Three different levels of damage are set for each fault type, with diameters of 0.1778mm, 0.3556mm and 0.5334mm. Under these three diameter fault conditions, the motor speed is 1797rpm, 1772rpm, 1750rpm and 1730rpm.

Tab.2. CWRU Fault set partitioning.

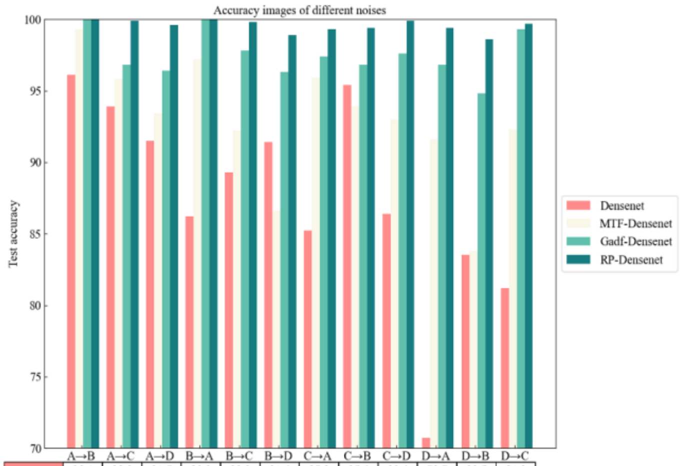
Transfer task	A	B	C	D
Rotational speed /rpm	1730	1750	1772	1797

4.2.1. Ablation contrast experiment

In order to verify the effectiveness of RP-Densenet in rolling bearing fault diagnosis, a series of ablation comparison experiments were designed to deeply explore the influence of different image coding methods and network structures on diagnostic performance. Several models, including standard Densenet, MTF-Densenet, Gadf-Densenet and complete RP-Densenet models, were constructed, and their fault diagnosis accuracy was evaluated through iterative training and repeated experiments. Experimental results show that the diagnostic accuracy of the model decreases after removing or replacing key components, demonstrating the importance of recursive graph coding and Densenet structure. The effectiveness of RP-Densenet is verified, and the effect of different coding and network structure on the performance is revealed.

Tab.3. CWRU Transfer learning diagnostic results

method	Mean diagnostic accuracy（%）	Standard deviation of accuracy（%）	Running time（s）
RP-Densenet	99.94	0.21	87.2
Gadf-Densenet	99.24	0.27	133.1
MTF-Densenet	98.67	0.41	141.7
Densenet	98.11	0.90	162.5



	A→B	A→C	A→D	B→A	B→C	B→D	C→A	C→B	C→D	D→A	D→B	D→C
Densenet	96.1	93.9	91.5	86.2	89.3	91.4	85.2	95.4	86.4	70.7	83.5	81.2
MTF-Densenet	99.3	95.8	93.4	97.2	92.2	86.6	95.9	93.9	93.0	91.6	83.8	92.3
Gadf-Densenet	100	96.8	96.4	100.0	97.8	96.3	97.4	96.8	97.6	96.8	94.8	99.3
RP-Densenet	100	99.9	99.6	100.0	99.8	98.9	99.3	99.4	99.9	99.4	98.6	99.7

Fig.9. CWRU Diagnostic results of different models.

4.2.2. Efficiency improvement

To test the effect of reducing diagnosis time by integrating MobileViTAttention module into the DenseNet bearing fault diagnosis model, multiple models were combined. Standard Densenet, MTF-Densenet, Gadf-Densenet and complete RP-DenseNet were included for parallel experiments. As shown in Figure (10), the MobileViTAttention module effectively reduces the number of overall calculation parameters of the model through its lightweight and efficient attention mechanism, thus maintaining or even improving the diagnostic accuracy while greatly reducing the computational complexity and resource consumption.

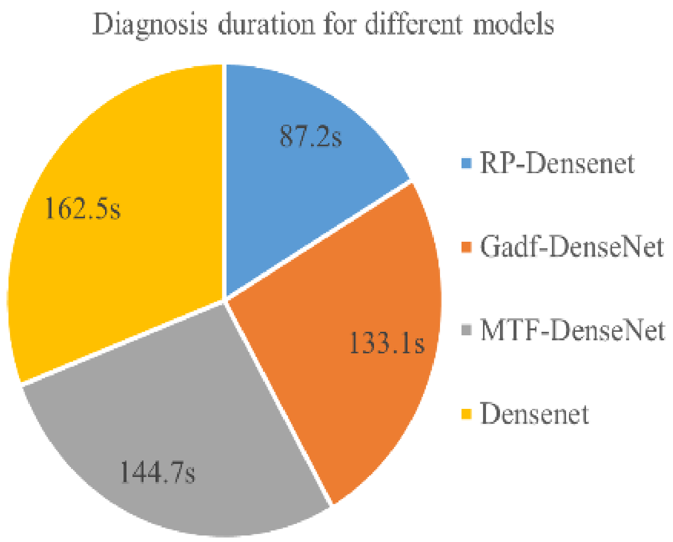


Fig.10. Diagnosis time of different models in CWRU dataset.

4.2.3. Data dimensionality reduction visualization

t-SNE is a nonlinear dimensionality reduction technique for converting high-dimensional data into a two-dimensional or three-dimensional visual form. In neural networks, t-SNE can be used to analyze the feature representation of the middle layer, which is mainly reflected in the following two aspects:

(1) Category boundary recognition: Through t-SNE visualization, the boundaries between different categories of data can be clearly seen, so as to understand how the network learns the category information of data.

(2) Clustering structure of feature space: t-SNE reveals the clustering phenomenon of similar samples in feature space, which helps to understand the representation of features in the middle layer and the classification mechanism of samples by the network.

By using t-SNE technology, the feature information of the output layer of the network is transformed and displayed on A two-dimensional plane, and the effect of the model on the CWRU migration task A→B is observed.

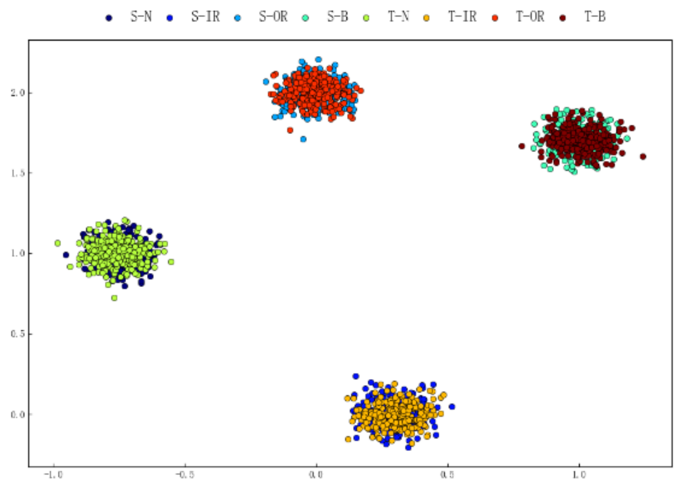
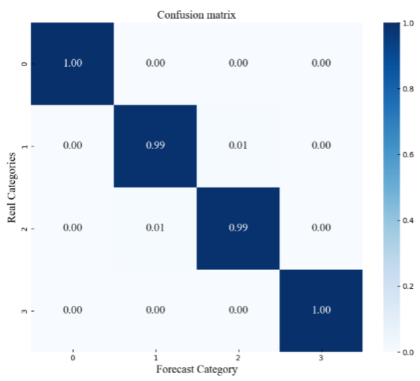


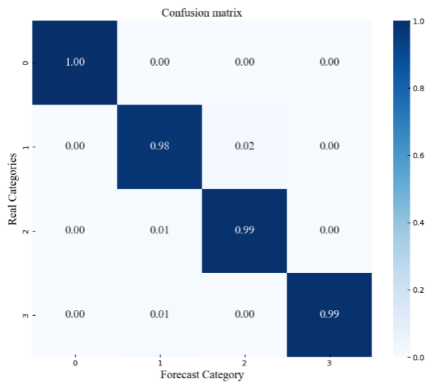
Fig.11. Visualization of the t-SNE dimensionality reduction of the model in the CWRU data A→B task.

4.2.4. Classification performance evaluation

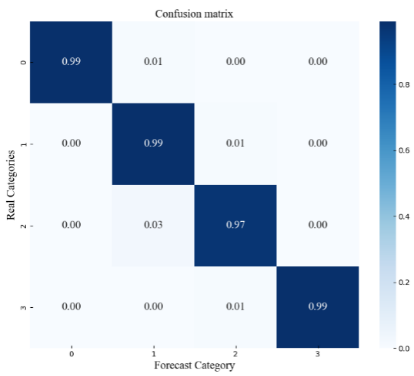
The confusion matrix experiment was introduced in the bearing failure data set test of Case Western Reserve University. After the experimental data were processed by the model, an intuitive confusion matrix heat map was generated to analyze the model's performance on the classification task more deeply.



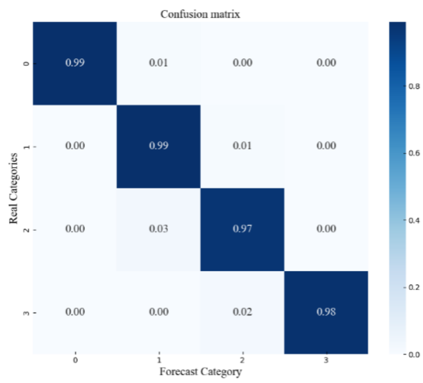
(a) RP-Densenet



(b) Gadf-Densenet



(c) MTF-Densenet



(d) Densenet

Fig.12. CWRU Task A→B confusion matrix heatmap.

4.2.5. Noise resistance analysis

The main impact of noise on fault diagnosis is that it will interfere with the detection of fault signals and reduce the accuracy of data, which may lead to wrong diagnosis results.

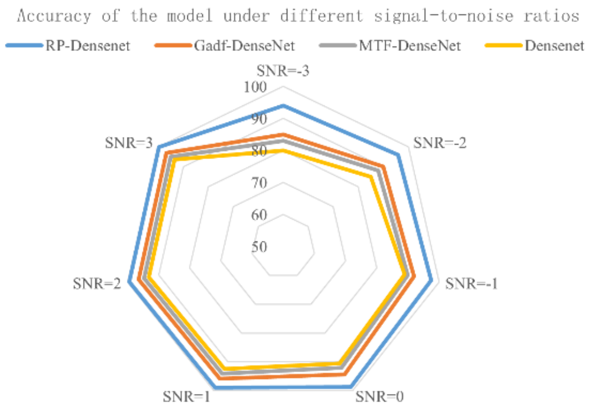


Fig.13. CWRU Task A→B Gaussian white noise accuracy images with different signal-to-noise ratios were added

Now, different intensity Gaussian white noise is added, and different models and improved DenseNet are used to conduct comparative experiments on A→B sample set to verify the advantages of the improved model. The sample difference is only whether there is noise reduction, and other Settings such as model parameters, network depth, and sample Settings are the same.

4.3. Jiangnan University bearing failure data set

The bearing fault dataset of Jiangnan University is an open data set for bearing fault diagnosis and predictive maintenance research. The data set contains rolling bearing failure data operating under different speed conditions, such as outer ring, inner ring and rolling element failure data.

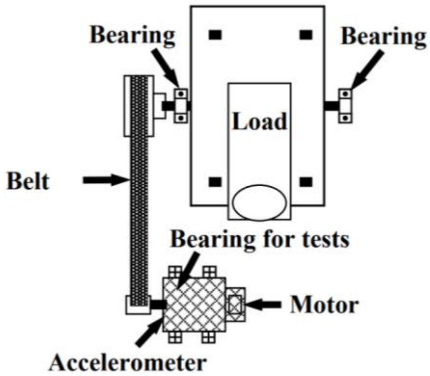


Fig.14. Mechanism diagram of the fault diagnosis test of the centrifugal fan system

As shown in Figure 14, the test bench is the mechanism diagram of the fault diagnosis test of the centrifugal fan system using the Mitsubishi SB-JR induction motor. The motor is 3.7KW three-phase induction motor, voltage 220V, motor pole number 4. The sampling frequency was 50kHz, and the bearing fault data were collected at 600rpm, 800rpm and 1000rpm respectively. The rotor was supported by two bearings, and the whole experimental device had a defective bearing, which was located on the output shaft of the motor. The defects are outer ring failure, inner ring failure and rolling element failure. The bearing fault data set of Jiangnan University was used to mainly verify the performance of the model in the task of cross-working condition migration. The data set was divided as follows.

Tab.4. JNU Fault set partitioning.

Transfer task	0	1	2
Rotational speed/rpm	600	800	1000

4.3.1. Ablation contrast experiment

The bearing data set of Jiangnan University also shows good fault diagnosis accuracy and short diagnosis time.

Tab.5 JNU Transfer learning diagnostic results

method	Mean diagnostic accuracy（%）	Standard deviation of accuracy（%）	Running time（s）
RP-Densenet	99.14	0.19	88.3
MTF-Densenet	98.42	0.42	134.9
GAF-Densenet	97.97	0.57	146.1
Densenet	97．35	0.86	157.5

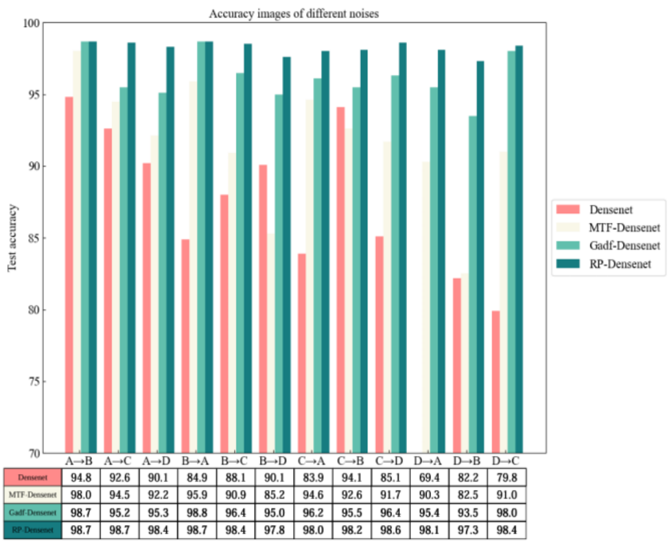


Fig.15. JNU Diagnostic results of different models.

4.3.2. Efficiency improvement

The bearing fault data set of Jiangnan University also reflects that the MobileViTAttention module speeds up the reasoning speed of the model, reduces the time of bearing fault diagnosis, and improves the real-time response ability of the model.

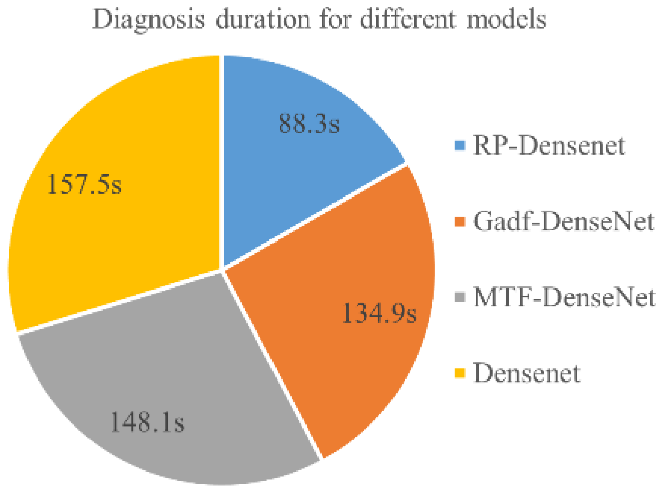


Fig.16. Diagnosis time of different models in JNU dataset.

4.3.3. Data dimensionality reduction visualization

Through t-SNE dimensional reduction visualization, it can be seen that the model is also excellent on the bearing data set of Jiangnan University.

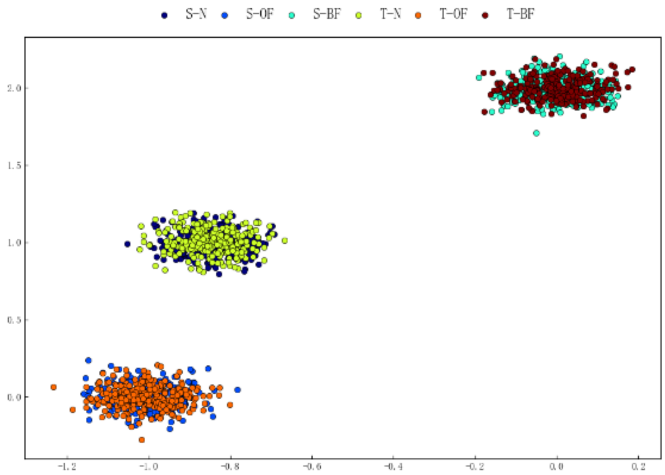
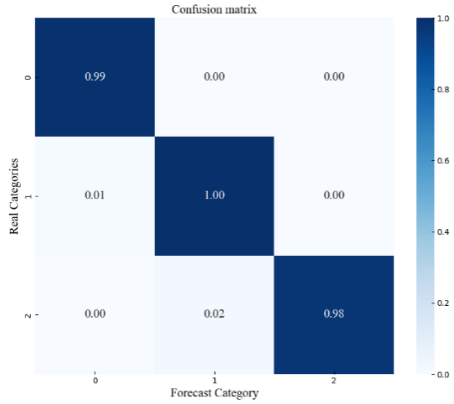


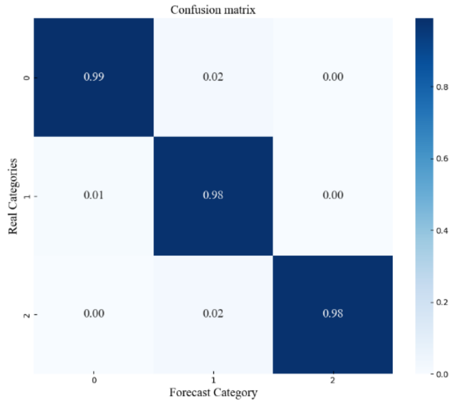
Fig.17. Visualization of the t-SNE dimensionality reduction of the model in the JNU data 0→1 task.

4.3.4. Classification performance evaluation

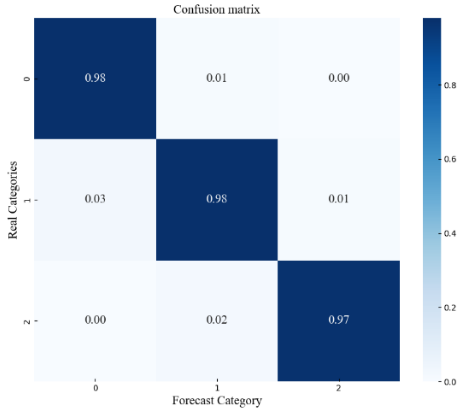
The confusion matrix experiment in the bearing fault data set test of Jiangnan University can more intuitively see the performance of the model in the classification task.



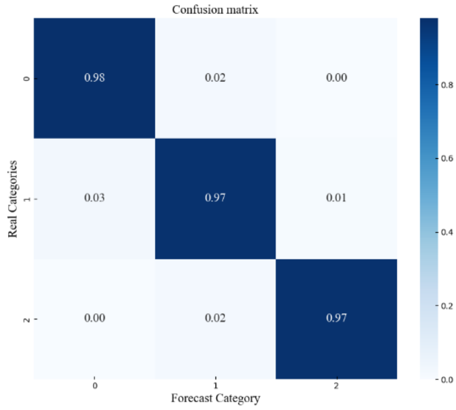
(a) RP-Densenet



(b) Gadf-Densenet



(c) MTF-Densenet



(d) Densenet

Fig.18. JNU Task 0⟶1 confusion matrix heatmap.

4.3.5. Noise resistance analysis

White Gaussian noise of different intensity was also added to the data of Jiangnan University, and different models were used to compare the 0⟶1 sample set with the improved DenseNet to verify the advantages of the improved model.

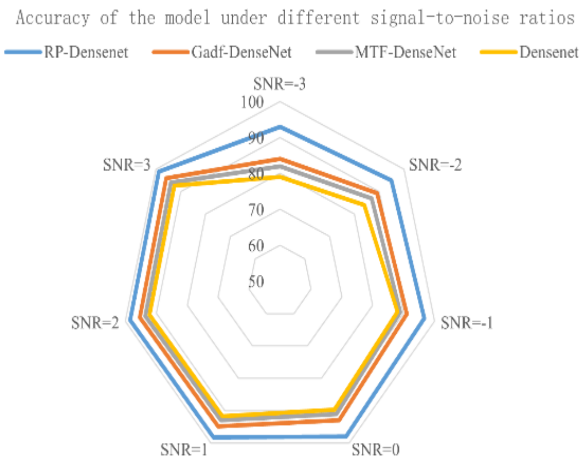


Fig.19. JNU Task 0⟶1 Gaussian white noise accuracy images with different signal-to-noise ratios were added.

5. Conclusion

Aiming at the problem that one-dimensional vibration signals ignore the time series characteristics and the marked data is scarce, which leads to the difficulty of fault identification and the decrease of classification accuracy in the target domain, this study proposes a method combining improved DenseNet and transfer learning. The one-dimensional vibration data is converted into two-dimensional data by RP technology, and the fault features in the source domain are automatically extracted by DenseNet embedded with MobileViTAttention module. By transfer learning, the fault feature information effectively extracted from the source domain is transferred to the target domain, so that the fault data in the target domain can be classified and recognized efficiently. The experimental results show that the proposed method has excellent performance in migration diagnosis for rolling bearings with variable operating conditions, and significantly improves the accuracy of fault identification, anti-noise performance and reduces the running time.

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