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Unbalanced Data Fault Diagnosis based on Double-flow Multiscale Feature Fusion

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Abstract: *Fault diagnosis is the research content that has attracted much attention at present, and it is of great significance to the engineering application in the field of the mechanical industry. The imbalance of data samples in the actual engineering of fault diagnosis leads to the low learning ability of network representation. A double-flow multiscale feature fusion strategy is proposed for intelligent fault diagnosis of rolling bearing under unbalanced data. First, the method preprocesses the original one-dimensional data based on the short-time Fourier transform (STFT) and oversampling method to obtain two-dimensional time-frequency map and optimize the distribution space of unbalanced data. Then, taking the convolution neural network and attention mechanism as the backbone network, a parallel double-flow network is designed to extract the characteristics of sequence data and time-frequency data respectively to obtain single-flow feature information of different scales. Finally, the output single-flow features are input to the MLP to fuse and infer the multiscale features of each data. The proposed model is verified on three kinds of open data sets. Through comparative experiments, ablation studies, generalization performance analysis, and other experiments, it is proved that the model is effective in the diagnosis of rolling bearing imbalance data.*

KEY WARDS: *Unbalanced data, Feature fusion, Fault diagnosis, Oversampling*

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I.INTRODUCTION

In complex and diverse modern industrial scenarios, rolling bearing usually operates in healthy conditions. However, in caseswhere catastrophic or accidental mechanical faults occur, unpredictable consequences may arise[1,2]. Intelligent algorithm represented [3-5] by deep convolution neural network has been widely used in the field of fault diagnosis. Zhang [6] proposed a new transfer learning method, the selective normalization multiscale convolutional adversarial network, which incorporated multiscale CNNs and improved the model's accuracy in intelligent fault diagnosis.Yin[7]proposed an optimized fault diagnosis method for wind turbine gearboxes with cosine loss LSTM neural network (Cos-LSTM) for intelligent fault diagnosis of the gearbox.

However, in practice, the running time of rolling bearing under normal is far longer than that under fault conditions, and normal samples are often easier to obtain, which leads to a serious imbalance between normal and fault sample data in model training. When the target data are unbalanced, the generalization performance on testing data drops significantly. This imposed negative impacts on data-driven fault diagnosis models.Therefore, it is very important to improve the recognition accuracy of minority classes under the condition of unbalanced data, which has also become the focus of machine learning and data mining research in recent years.

Current research[8-10] tackles this issue with methods falling into two categories: data synthesis and algorithm optimization. The aspect of algorithm optimization[11-12], is mainly to improve the recognition accuracy of the classifier by constructing new algorithms or original classification algorithms. The typical cost-sensitive optimization algorithm[14] is to pay a high cost for the loss of a few samples in the iterative process of the algorithm.Although the algorithm optimization method can also effectively improve the classification effect of unbalanced data, in most cases, the applicability is relatively weak because it is difficult to accurately estimate the misclassification cost that is most suitable for the characteristics of data sets. For techniques based on data synthesis[15,16], a simple way is to duplicate existing samples to increase the sample size of minority classes or reduce the sample size of majority classes to balance the data, thereby achieving better classification performance. However, the random sampling method has certain defects. The random oversampling may cause over-fitting due to too many samples, and the random under-sampling may cause the loss of some important information due to the reduction of samples. To overcome the above shortcomings, many scholars have proposed a series of improved sampling methods, such as SMOTE and its improved methods.

SMOTE [17] and its improved method [18,19] have significantly improved compared with the random oversampling method, but in essence, they start from the local neighborhood of a few samples and synthesize new samples by linear interpolation. They do not make full use of the distribution information of the data, resulting in the generated new samples cannot better simulate the distribution characteristics of the real data, and the classification performance of the unbalanced data is limited.The research shows [20-23] that the information fusion method can be used in the deep network to carry out a certain feature fusion strategy for the input data, which can fully obtain the global and local feature information of the data, and further promote the target learning task of the network.Tang [24] uses fully integrated empirical mode decomposition (CEEMDAN) to extract time domain features and fast Fourier transform (FFT) to extract deep frequency domain features, and finally selects the best feature subset for fusion diagnosis.Liu [25] proposed a multi-dimensional feature fusion and ensemble learning model (MFF-GBFD) under the background of industrial data noise and insufficient fault samples. Multi-dimensional feature fusion is extracted by principal component analysis, and the model is trained under the integrated learning framework. Based on multi-feature fusion, it promotes the feature learning process of the network, reduces the situation that leads to feature loss, and considers the complex information hidden in the data.

Given the above problems, this paper focuses on the improvement and research from data processing and feature learning strategies. A double-flowmultiscale feature fusion diagnosis strategy is innovatively extracted for fault diagnosis of rolling bearing data with unbalanced data. The main contributions of this paper are as follows:

⑴ At the data level, the unbalanced original one-dimensional sequence data is converted into a two-dimensional time-frequency map through the STFT algorithm, and two data sets of different scales are obtained. Then, the SMOTE algorithm is used to over-sample and balance the original one-dimensional data and two-dimensional time-frequency map to enhance the feature extraction ability of the network and assist the target diagnosis task of the network.

⑵ For the feature learning strategy, the designed double-flow network first extracts single-scale feature information in the lower layer, and then fuses multiscale features in the middle layer, and converts them into higher-level representation information to obtain effective decision results at the upper level.

⑶ The contrast experiment, generalization test, ablation study, and other experiments were designed, and the rationality of model structure design and loss function design was verified by visual analysis.

The rest of this article is organized as follows. Section 2 describes the proposed method in detail. The third section verifies the effectiveness of the proposed method through experiments and results analysis. Finally, section 4 summarizes the proposed methods and puts forward prospects for our future research.

II. THE PROPOSED METHOD

2.1 Double-flow multiscale feature fusion network （DMFFN）

Aiming at the imbalance of rolling bearing data of mechanical equipment, this paper provides a new idea of double-flowmultiscale feature fusion diagnosis. The model structure is shown in Fig.1.First, before the unbalanced one-dimensional vibration sequence data enters the double-flow network, STFT is applied to transform the data to obtain two-dimensional time-frequency map data. Then, the improved SMOTE method is introduced to preprocess the original one-dimensional sequence data and the transformed two-dimensional time-frequency data respectively to obtain two balanced but different scale single-flow samples. This step gives priority to optimizing the category imbalance problem from the data level to avoid the problem of network learning difficulty caused by data scale deviation. Then, single-flow samples of different scales are simultaneously input into the double-flownetwork for feature learning. In the double-flow network, the data is convolved by the CNN network for many times and the attention of the SENet channel is enhanced to obtain high-level features of different scales. Finally, it is input into the fusion diagnosis network, and the decision recognition is carried out after multi-layer perceptron fusion.

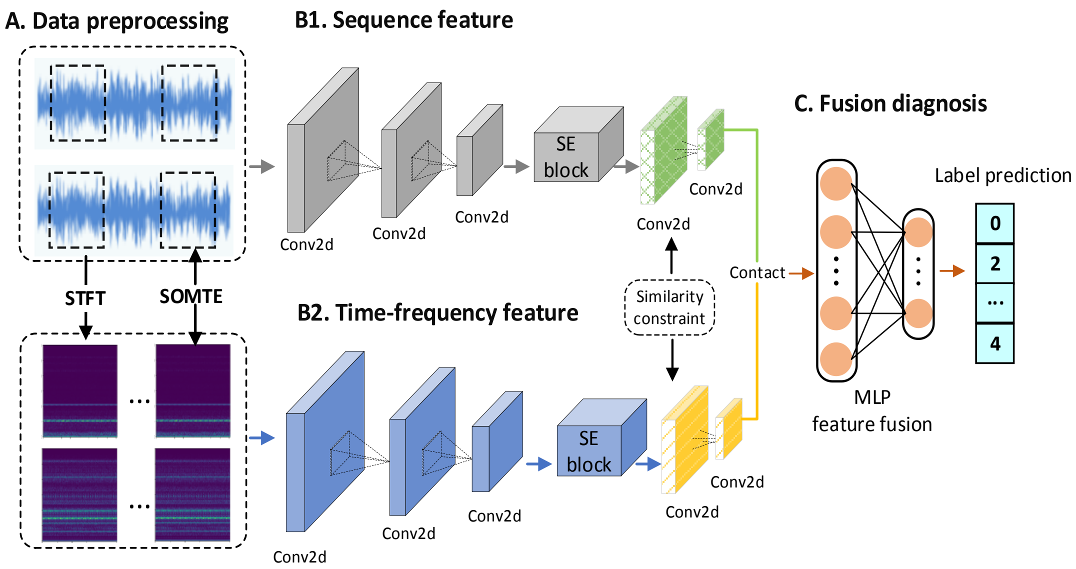

Figure 1: DMFFN network.

2.2Data preprocessing

First, the unbalanced original vibration data is converted into a time-frequency diagram by using the short-time Fourier transform (STFT) [26], considering the time domain and frequency domain, which preserves more sufficient information and more complex structure distribution than one-dimensional signal. STFT is a time-frequency analysis algorithm for time-varying and non-stationary signals. The spectrum obtained is a two-dimensional matrix containing the characteristic spectrum of time and frequency domain information. The basic calculation formula is as follows:

$$S_{STFT_z}(t,f)=\int_{-\infty}^{\infty}[z(u)\,\mathrm{g}(u-t)]\mathrm{e}^{-j2\pi fu}\,du \tag{1}$$

Where $z(u)$ is the timing signal and $\mathrm{g}(u-t)$ is the window function. The variables t and f are the time and frequency resolution, and the formula is as follows:

$$t=[\frac{N_1-N_0}{N_2-N_0}] \tag{2}$$

$$f=\begin{cases}N_3/2+1, N_3 \textit{ is even}\\ (N_3+1)/2, \; N_3 \textit{ is odd}\end{cases} \tag{3}$$

Where N_0 is the window function overlap width, N_1 is the sample length, N_2 is the window function width, and N_3 is the intercepted signal length.

According to (2) and (3), the signal after STFT is a 2-D data matrix, and each matrix is normalized to an interval [0,1] to accelerate the convergence of the training process. Then, the SMOTE method is used to balance the original one-dimensional original signal (x_o) and two-dimensional time-frequency map (x_t) to obtain various data sets of category equalization. The main idea of SMOTE is to start from the local neighborhood of the minority sample points and use the random linear interpolation method to synthesize new minority samples between the minority samples and their K-nearest neighbor samples. The sample synthesis formula is:

$$x_m^{'}=x_m+\varepsilon*(x_j - x_m)\,,\, m\in\{o,t\} \tag{4}$$

Where $x_m^{'}$ is the composite minority sample, x_m is the m minority sample, and x_j is the j nearest neighbor sample of the m minority sample; ε is a random number between [0,1].

2.3Network structure

The double-flow structure proposed in this paper consists of two feature extraction networks with the same structure, which can be used to extract the features of one-dimensional original data and two-dimensional time-frequency graphs at the same time, to obtain two single-flow features of different scales. The structure mainly includes a two-dimensional convolutional neural network (2D-CNN) and channel attention module (SENet). 2D-CNN includes convolution layers (Conv2d), normalization layer (BN), pooling layer (P), and

ReLU activation function. The detailed structure of the network is illustrated in Fig.2.

The original one - dimensional vibration signal and two-dimensional time-frequency graph are respectively input into the double-flow network. Among them, the original vibration signal is also suitable for two-dimensional convolution calculation after parameter setting. Therefore, the calculation process of the original signal is the same as that of the converted time-frequency graph. In the *l*-th layer of the 2D convolution computation, the convolutional feature is obtained by the dot product of the *i*-thsegment signal x_i^l, and the convolution kernel k_{ij}^l, as:

$$c_j = \mathrm{ReLU}(\sum_{i=1}^{n} k_{ij}^l * x_i^l + b_j^l) \tag{5}$$

Where $*$ is the 2D convolution operator, $\mathrm{ReLU}(\cdot)$ is the activation function, n is the number of kernels, b_j^l is the corresponding biasand c_j is the j-th output node of the convolutional layer.

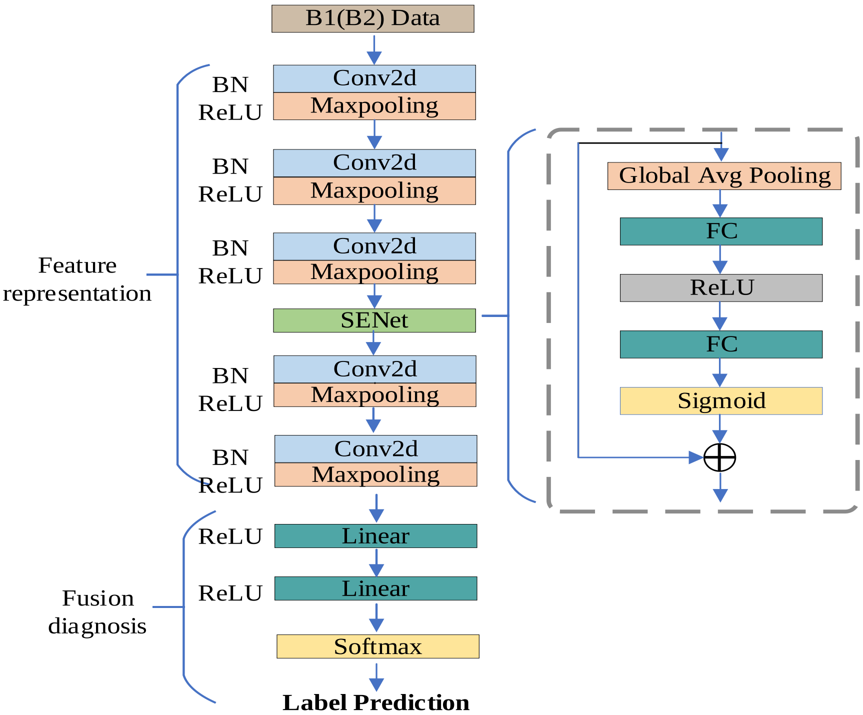

Figure 2: DMFFNnetworkof the feature representation and fusion diagnosis.

To avoid the gradient vanishing and exploding, the data are standardized by BN in the convolutional layers to accelerate the convergence of weight parameters as:

$$\eta_i = \gamma_i \hat{x}_i + \beta_i \tag{6}$$

Where each scaler feature is normalized independently by the mean and variance as $\hat{x}_i = (x_i - E[x_i]) / \sqrt{Var[x_i]}$. To prevent the learned feature distribution from changing during normalization, and to scale and shift the normalized values, $\gamma_i = \sqrt{Var[x_i]}$ and $\beta_i = E[x_i]$ are usedin each x_i learning step, which participatesin the training of parameters of the primitive model. $E[x_i]$ is the mean of each unit, and $Var[x_i]$ represents the variance.

Each convolutional layer is followed by a poolinglayer. We select the maxpooling function to obtain the maximum value in a specific subsegment, to reduce the convolutional feature dimension, and to make the learned feature shifts invariant. After convolution, normalization, and pooling several times, the input signal is mapped to the feature graph of the third pooling layer, and then input to the SENet module to redistribute the weight among the features.SENet selectively enhancesbeneficial channels basedon global information and achieves adaptive calibrations of feature channels.

In our proposed model, the input of SENet is compressed through global averaging pooling (i.e.,the $F_{eq}(\cdot)$ operation), and is then dimension-reduced and dimension-increased by two FC layers (i.e., the $F_{ex}(\cdot)$

operation), resulting ina 2D vector of the original samples. Then, the weights for each feature channel are generated, and the 2D vector is multiplied by the corresponding channels of the multiple feature maps outputted by the third convolutional layer (i.e., the dot product $F_{scale}(\cdot)$ operation):

$$z_c = F_{eq}(\mathrm{u}_c) = \frac{1}{W \times H}\sum_{i=1}^{W}\sum_{j=1}^{H}\mathrm{u}_c(i,j) \tag{7}$$

$$s = F_{ex}(\mathrm{z},\mathrm{W}) = \sigma(g(\mathrm{z},W)) = \sigma(W_2\delta(W_1 z))\ W_1 \in R^{\frac{C}{r}\times C},\ \ W_2 \in R^{C\times\frac{C}{r}} \tag{8}$$

$$x_c = F_{scale}(u_c, s_c) = s_c \cdot u_c \tag{9}$$

Where u_c denotes the c-th 2D matrix in U, U is a 3D matrix obtained throughthe conversion of the CNN, i.e. C feature maps of $H \times W$, σ is the sigmoid function, δ is the ReLU activation function, $W_1 z$ is the full-connection operation, where the dimension of W_1 is $(C/r)\times C$ and the dimension of W_2 is $C\times(C/r)$, and r is a scaling parameter.

Through the above operation, the input data is converted into different scale features representation. Then, the single-flow features are spliced and input into the multi-layer perceptron (MLP) to complete the multiscale feature fusion and diagnosis.

$$F = MLP\left(x_o \oplus x_t\right) \tag{10}$$

Where, F is the inferred representation, x_o is the scale feature of the original data, x_t is the scale feature of the time-frequency map, and $\oplus$ represents the feature stitching operation.

2.4Optimization objective

Fully extracting the interactive information between multiscale features before performing the fusion task can effectively reduce the burden of feature fusion and improve the performance of the model. Adding distance metric constraints between multiscale feature representations is a common invariant feature extraction method. Therefore, to reduce the technical complexity, the mean square error function is used here as the similarity loss function：

$$L^{sim} = \left\|x_o - x_t\right\|_2^2 \tag{11}$$

since the essence of rolling bearing fault diagnosis is the application of classification tasks in t industrial field, the cross-entropy loss function is adopted as the target loss:

$$L_{task} = -\sum_{i=0}^{N} y_i \log F_i \tag{12}$$

where, y_i is the fault type label of the sample m, F_i is the network inference result of the sample m .Combining similarity loss and target loss, the joint loss function designed in this paper is used for network training and learning, and is defined as follows:

$$L_{total} = \alpha L_{task} + (1-\alpha)L^{sim} \tag{13}$$

where, α -the loss function regulation factor is used to adjust the contribution of target loss and auxiliary loss.

III. MODEL VALIDATION

3.1 Experimental steps

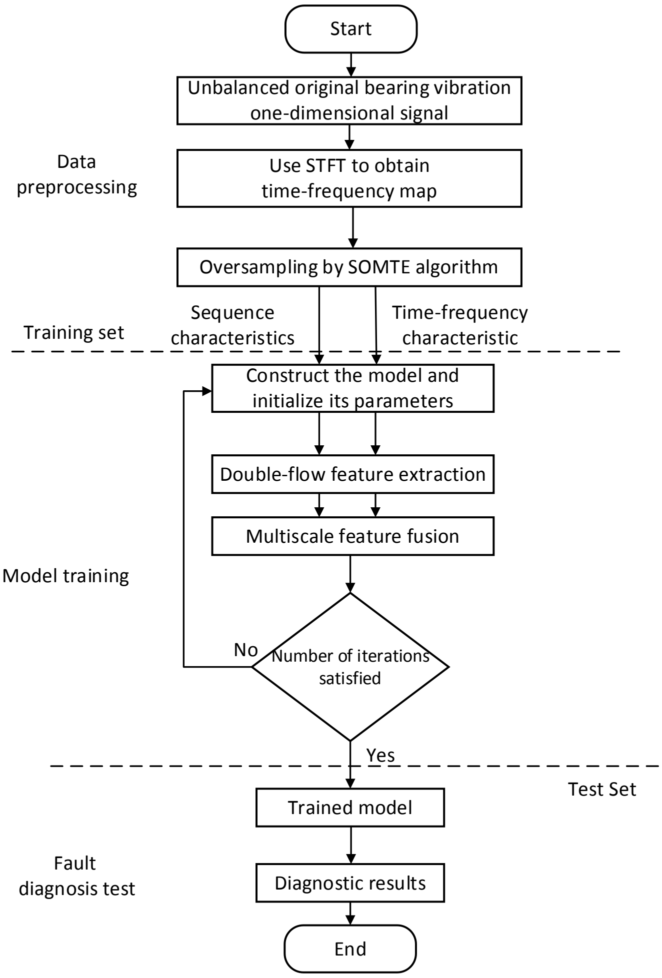

Figure 3: Flow chart of proposed model experiment

3.2Introduction of the Experimental Data

Four types of experiments are designed in this section to verify the fault diagnosis performance of the model for unbalanced data.We used the PU bearing data set [27], in which authentic fault data were generated in accelerated lifetime experiments. Bearing casing vibration signals were collected by piezoelectric acceleration sensors with a sampling frequency of 64 kHz. Bearing working condition categories include the normal type and three types of failures: single-point fault, repeating fault, and multiple faults.

For unbalanced data, we set four categories as normal (N), fault 1 (F1), fault 2 (F2), and fault 3 (F3). The number of samples for each category is set to N=F1=F2=F3 in the experiment. 80% of the samples are used for training and 20% for testing. The dimension of the sample is 1024, the training period is 100, and the batch size is 64. The distribution and imbalance of experimental data are shown in Table 1.

Table 1. **Groups of unbalanced data**

Data(PU)	N	F1	F2	F3
Factor	Normal	Out ring	Inner ring	Out and Inner
Case1	5000	500	500	250
Case 2	5000	500	500	100
Case 3	5000	500	500	50
Case 4	5000	500	500	25

3.3Analysis of experimental results

Experiment 1: Comparison of different pretreatment methods

After determining the most suitable learning strategy, two other data preprocessing methods are adopted: 2D transform (2T) [28] and wavelet transform (WT) [29], which are compared with STFT to verify the advantages of ST-DMFFN based on STFT. The 2T method reconstructs the time series signal by row to obtain the 2-D matrix and converts the samples with fixed size into time-frequency maps. WT is to decompose the signal into a series of wavelet functions with different scales and times after translating the basic wavelet functions into sequence data. In addition, neither 2T nor WT methods need to set any parameters.

Table 2.**Comparative experiments**

Method	Case1	Case2	Case3	Case4
2T-DMFFN	77.1	73.8	69.5	65.7
WT-DMFFN	98.6	96.4	96.0	95.8
ST-DMFFN	99.1	98.3	98.7	98.2

It can be seen from Table 2 that this experiment not only provides a comparison between various methods but also verifies the model diagnosis performance under different balance ratios. The results show that 2T-DMFFN is not suitable for the distribution of unbalanced data sets. Compared with other methods, there is a significant gap in data preprocessing and fault diagnosis performance. With the increase of sample imbalance, the diagnosis result of WT-DMFFN decreases gradually, while the ST-DMFFN model shows stable robustness and a small fluctuation range. Therefore, this experiment confirmed the advantages of combining STFT with DMFFN.

Experiment 2: Comparison of different sampling methods

Compare the oversampling method SMOTE (SOM-DMFFN) applied in this paper with the original data (OR) and ADASYN [30]. The experimental results are shown in Table 3.

Table 3. **Comparative experiments**

Method	Case1	Case2	Case3	Case4
OR-DMFFN	73.5	71.8	66.5	63.9
ADA-DMFFN	98.3	96.9	97.1	96.5
SOM-DMFFN	99.1	98.3	98.7	98.2

By analyzing the experimental results of different unbalanced data sets, the sampling method applied by the proposed model is superior to other oversampling methods. Especially in the case of serious imbalance. The reason for the worst performance of OR-DMFFN is that the original data is directly input into the network training under the unbalanced condition, and the network cannot be correctly learned, resulting in the insufficient fitting. It is thus verified that the fusion diagnosis strategy based on SMOTE oversampling method in this paper can effectively solve the problem of data distribution differences in unbalanced data sets, and is outstanding when the categories are seriously unbalanced.

Experiment 3: Generalization performance experiment

To further verify the comprehensive performance of the model, this section designs the generalized performance experiment and introduces the bearing data set of Jiang Nan University and the bearing data set of Western Reserve University to test the model.The CWRU bearing data set [31]is provided by Case Western Reserve University. We utilized its vibration signals, which were collected by acceleration sensors mounted on outer casings with a sampling frequency of 12 kHz. The JNU data set [32]consists of orientation data acquired by Jiang Nan University, China. The vibration signals that we used were collected by acceleration sensors with a sampling frequency of 50 kHz.The experimental results are shown in Fig.4.

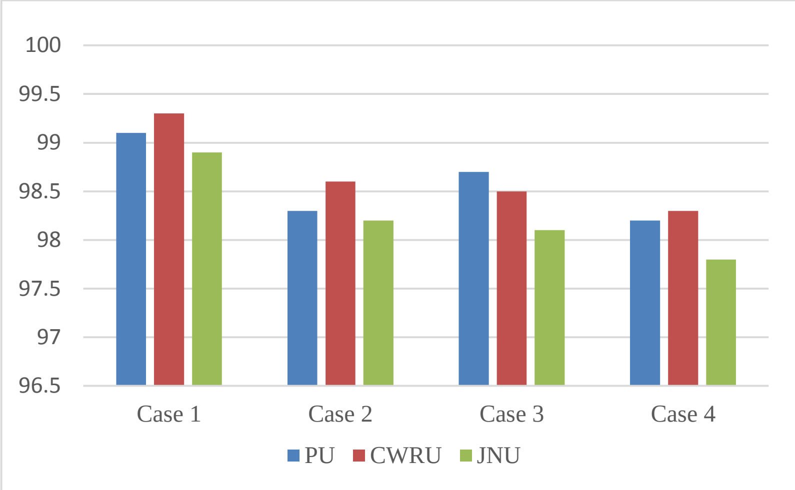

Figure 4: Generalization performance experiment

The generalization performance experiment shows that the DMFFN model achieves good and stable bearing fault diagnosis accuracy on the other two unbalanced data sets. Among them, the quality of CWRU's bearing data set is high, which promotes the feature learning ability of the network, and the final overall diagnosis result is better. Finally, it shows that the proposed method has good generalization performance and verifies the superiority of the proposed double-flow multiscale feature fusion model.

Experiment 4: ablation investigation

The comparative analysis verifies the effectiveness of the model, but it lacks the rationality analysis of the network structure and loss function design. Therefore, this section uses ablation experiments to carry out further quantitative analysis of the model. This section verifies the diagnostic ability of the model to categorize under unbalanced data through the visualization of the confusion matrix. Similarly, the data set of the experiment is verified by case 4.

a. Without STFT preprocessing

b.Without similarity constraint

c. Without SENet module

d. None

Figure 5: Ablation investigation

As shown in figure5, it is easy to see the accuracy of each category in each ablation experiment. Among them, the lack of STFT and similarity loss hurts the network learning sufficient feature information of different scale features and enhances feature relevance, further reducing the diagnostic accuracy of the network. The ECA module and LSTM module can help the model learn the spatiotemporal characteristics of the input signal to optimize the network performance. As can be seen from Fig.5 (d), our proposed model has the highest classification accuracy and is very effective in classification performance. Therefore, our loss function design and network architecture are feasible.

Ⅳ. CONCLUSIONS

This paper proposes a rolling bearing fault diagnosis model based d on a double-flow multiscale feature fusion network (DMFFN) based on unbalanced data, and the effect is better than that of single feature diagnosis and recognition. The network is mainly composed of three parts: data preprocessing, double-flowmultiscale feature extraction network, and fusion inference module. STFT and SOMTE are used for data preprocessing. The double-flow network extracts multiscale features of the original one-dimensional data and two-dimensional time-frequency map in parallel through convolution and channel attention; the MLP module is used to fuse and infer multiscale features. This method is not limited to two basic assumptions in traditional machine learning: (1) satisfying the sample equilibrium of multi-class experimental data; (2) Only with good data quality can a robust network be trained. The validity of the model was reasonably verified by the contrast experiment, generalization experiment, and ablation experiment. In the future, the research on heterogeneous unbalanced data of multi-sensor will be discussed to further improve the application of intelligent fault diagnosis.

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