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# Multisensor Feature Fusion Based Rolling Bearing Fault Diagnosis Method

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**Abstract:** To fully utilize the fault information and improve the diagnosis accuracy of rolling bearings, a multisensor feature fusion method is proposed. The method contains two steps. First, the intrinsic mode function (IMF) of each sensor vibration signal is calculated by variational mode decomposition (VMD), and the redundant information such as noise is eliminated. Then, the time-domain, frequency-domain and multiscale entropy features are extracted based on the preferred IMF and fused into one multidomain feature dataset. In the second step, the deep autoencoder network (DAEN) is constructed and the multisensor fusion features of the first step are used as input of the DAEN, and the multisensor fusion features are further extracted and classified. The experimental results show that the proposed model has a higher classification accuracy compared with the existing methods.

**Keywords:** fault diagnosis; autoencoder network; multisensor; feature fusion; rolling bearing

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## 1. Introduction

As a critical component of rotating machine, rolling bearings have the advantages of high efficiency, low friction resistance and convenient assembly. Furthermore, their performance directly affects the operation of all the equipment. Therefore, knowing how to fully exploit the fault features from the complex vibration signals and carry out pattern recognition is of great significance [1,2].

The mainstream methods of fault diagnosis only focus on the application of a single sensor [3–5]. The commonly used sensor is the vibration acceleration sensor, which can measure the relationship between the vibration amplitude and time. However, more and more studies have shown that, for a complex mechanical system, the fault information contained in a single sensor is limited, and accurate condition monitoring and fault diagnosis cannot be performed [6–8]. The application of multiple sensor technologies in fault diagnosis makes it possible to study fault diagnosis based on multiple sensors. Wang et al. [9] proposed a mixture of Gaussians and variational auto-encoders (Mix-VAEs) fault diagnosis method, which can fully utilize the redundancy and complementarity of multisensor information. Chen et al. [10] proposed an stack auto-encoder and deep belief network (SAE-DBN) based multisensor fusion method, and verified the effectiveness through a bearing fault experiment. Shi et al. [11] proposed a two-stage multisensor fusion method to achieve accurate diagnosis of hydraulic directional valve faults. The above studies show that compared with a single sensor, multisensor information fusion technology can further improve the accuracy and reliability of diagnosis.

Multisensor information fusion technology includes data-level fusion, feature-level fusion and decision-level fusion, which have their own advantages and limitations [12–14]. The advantage of data-level fusion is that the raw signals of multiple sensors can be directly fused. Unfortunately, the raw data usually contains a lot of redundant information, and the data-level fusion method cannot take full advantage of the complementarity between the information of multiple sensors. Furthermore, the interpretability of the data is poor. Jing et al. [15] directly fused data from multisensors to construct a deep network for planetary gearbox fault diagnosis. Huang et al. [16] proposed a multisensor data fusion method to solve the problem of multisource remote sensing data fusion.

In order to make up for the deficiencies of data-level fusion methods and eliminate redundant information from multiple sensors, data-level fusion methods can be combined with feature extraction methods. First, the data from each sensor is transformed into a high-dimensional feature representation, and then, fusion is performed at the feature level, and this fusion method is called feature-level fusion [17,18]. Li et al. [19] proposed a fault diagnosis method based on a feature fusion covariance matrix and Riemann kernel ridge regression. Wang et al. [20] proposed a multisource sensor feature fusion method based on a convolutional neural network for mechanical fault diagnosis. Jiang et al. [21] extracted various entropy values of vibration signals using information entropy theory, and established a feature-level fusion model to classify faults. One of the advantages of feature fusion is that it can flexibly choose where to fuse, but it cannot eliminate the effect of high correlations between different sensor features.

In decision-level fusion, the basic learning model is first trained with different sensor signals, and then the output results of multiple models are fused through decision strategies. The errors of fusion models come from different basic learning models, which are often ir-relevant and do not affect each other, and will not cause further accumulation of errors. Therefore, the decision-level fusion method is favored. Common decision fusion methods [22,23] include the voting method and D-S evidence theory. Li et al. [24] proposed an enhanced weighted voting combination strategy with specific category threshold to realize multisensor decision fusion. Basir et al. [25] constructed a multisensor-based model according to D-S evidence theory to solve the problem of engine fault diagnosis. Zhao et al. [26] proposed a new distributed distance measurement method to measure the conflict between evidence based on an improved evidence theory algorithm. The decision-level fusion method is very sensitive to the selection of voting fusion rules, which directly determines the fusion result.

For the fault diagnosis of multisensor fusion, a unified and effective fusion model and algorithm has not yet been established, and various proposed models are still in the exploratory stage. From the above discussion, it can be seen that feature-level fusion is more flexible and convenient, not only to select information that can characterize fault features, but also to fuse at multiple locations. Furthermore, deep learning has the ability to learn features directly from raw signals, which largely overcomes the loss of effective information in feature-level fusion. Therefore, this paper proposes a multisensor feature fusion method combined with feature-level fusion and the deep learning method, and applies them to the fault diagnosis of rolling bearings under different working conditions. The proposed feature fusion method provides a more effective means for the deep mining of fault signals. The main contributions of this paper are as follows:

(1) A multisensor signals-based feature fusion method is proposed for one-dimensional vibration signals.
(2) The vibration signal of each sensor is preprocessed with VMD, and the time domain, frequency domain and multiscale entropy features of the signal are extracted and fused into one multidomain feature dataset.
(3) To promote further fusion of features, a novel deep autoencoder network is proposed for feature extraction and classification.

The rest of the paper is organized as follows. Section 2 reviews the AE. In Section 3, the proposed model is described in detail. Section 4 gives a detailed analysis and discussion of the experimental diagnosis results of rolling bearings. Section 5 presents the conclusions and possible future research directions.

## 2. Theoretical Basis

*Autoencoder*

Autoencoders (AE) can minimize the reconstruction error of input and output and are unsupervised neural networks. The structure of AE is shown in Figure 1. It consists of an input layer, a hidden layer and an output layer. The input layer and the hidden layer constitute the encoder, and the hidden layer and the output layer constitute the decoder. The encoder converts the high-dimensional input data into a low-dimensional feature representation, and the decoder converts the feature representation into a reconstructed form of the input data.

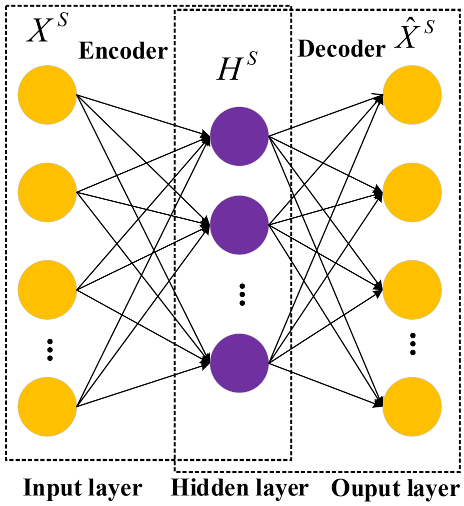



**Figure 1.** Structure of AE.

The encoder maps raw input signal **X** to the hidden layer feature **H**. The process is as follows:

$$\mathbf{H} = r_f(\mathbf{W}\mathbf{X} + \mathbf{b}) \tag{1}$$

The decoder reconstructs the hidden layer feature **H** to obtain the output vector $\hat{\mathbf{X}}$. The process is as follows:

$$\hat{\mathbf{X}} = r_g(\mathbf{W}'\mathbf{X} + \mathbf{b}') \tag{2}$$

where $\mathbf{W}$ and $\mathbf{W}'$ are the weight matrix, $\mathbf{b}$ and $\mathbf{b}'$ are the bias matrix $r_f$ and $r_g$ are the activation function.

The reconstruction error of AE is:

$$L(\mathbf{X}, \hat{\mathbf{X}}) = \frac{1}{2}\|\mathbf{X} - \hat{\mathbf{X}}\|^2 \tag{3}$$

where $\|\bullet\|$ represents the norm.

Therefore, the total loss function for $S$ sample is:

$$J(\mathbf{W}, \mathbf{b}) = \frac{1}{S}\sum_{n=1}^{S} L(\mathbf{X}, \hat{\mathbf{X}}) \tag{4}$$

## 3. Proposed Method

In this section, a feature fusion model based on multisensor signals is proposed and applied to rolling bearing fault diagnosis.

### *3.1. Fusion Model Architecture for Multisensor Signals*

The proposed method consists of two steps. The first step is multisensor feature fusion, where the IMF of each sensor vibration signal is calculated by VMD [27]. Then, time-domain, frequency-domain and multiscale entropy features are extracted based on the preferred IMF and fused into a multidomain feature dataset. In the second step, the DAEN is constructed and the multisensor fusion features of the first step are used as inputs of the DAEN. Then, the multisensor fusion features are further extracted and classified.

### *3.2. Implementation Process*

#### 3.2.1. Multisensor Feature Fusion

The proposed feature fusion method is as follows:

(1) The vibration signal $\mathbf{X}^1{}_{l\times1}, \mathbf{X}^2{}_{l\times1}, \cdots, \mathbf{X}_{l\times1}{}^n$ is collected from $n$ sensors of different directions, where $l$ is the sample length.
(2) Take the data length $i$ as a sample and divide $\mathbf{X}^1{}_{l\times1}, \mathbf{X}^2{}_{l\times1}, \cdots, \mathbf{X}_{l\times1}{}^n$ into $\mathbf{X}^1{}_{m\times i}$, $\mathbf{X}^2{}_{m\times i}, \cdots, \mathbf{X}^n{}_{m\times i}$, where $m$ is the number of samples.
(3) Using the VMD to decompose $\mathbf{X}^1{}_{m\times i}, \mathbf{X}^2{}_{m\times i}, \cdots, \mathbf{X}^n{}_{m\times i}$, a number of IMF components of each sensor are obtained, and base on the decomposition results, the first few components already contain the main information of the raw signal [28], so in this paper, we take the modal number $k = 3$ and decompose it to obtain $\mathbf{X}^1{}_{m\times3\times1024}, \mathbf{X}^2{}_{m\times3\times1024}, \cdots$, $\mathbf{X}^n{}_{m\times3\times1024}$.
(4) Feature extraction is performed for IMF components, and 12 time-domain features and five frequency-domain features [29] are extracted for each IMF component. To further reflect the degree of self-similarity and complexity of vibration signals under different scale factors of the same time series, five multiscale entropy values are extracted for each IMF component, denoted as $\mathbf{X}^1{}_{m\times3\times22}, \mathbf{X}^2{}_{m\times3\times22}, \cdots, \mathbf{X}^n{}_{m\times3\times22}$.
(5) The raw feature multidomain set is formed by fusing the proposed features, denoted as $\mathbf{X}^1{}_{m\times66}, \mathbf{X}^2{}_{m\times66}, \cdots, \mathbf{X}^n{}_{m\times66}$, and further fusing the raw feature multidomain set of sensors in each direction to obtain $\widetilde{\mathbf{X}} = \left[\mathbf{X}^1{}_{m\times66}, \mathbf{X}^2{}_{m\times66}, \cdots, \mathbf{X}^n{}_{m\times66}\right], \widetilde{\mathbf{X}} \in \mathbb{R}_{m\times66\times n}$.

#### 3.2.2. Deep Feature Learning and Classification

To enhance the performance of multisensor feature fusion, the DAEN model is proposed for deep feature learning and classification in this section. The proposed DAEN model is a multilayer neural network, which is composed of multiple stacked AE and a Softmax classification layer. The structure of DAEN is shown in Figure 2.

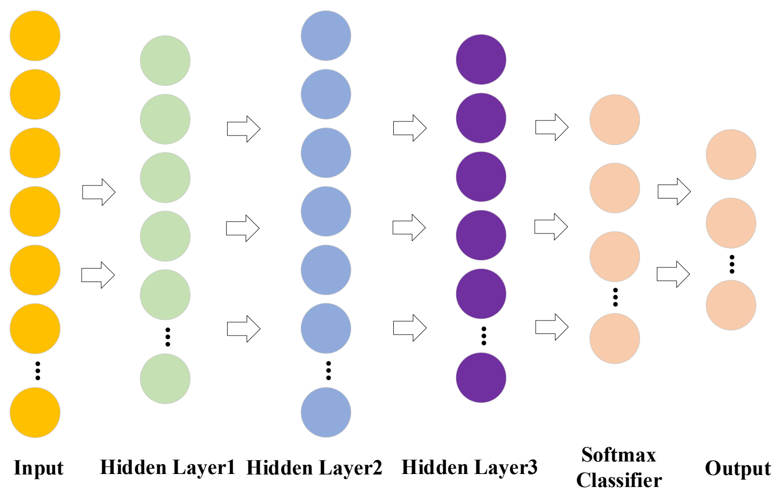



**Figure 2.** Structure of the proposed DAEN.

DAEN uses the Sigmoid activation function for nonlinear mapping [30]. The Sigmoid activation function is defined as follows:

$$\text{Sigmoid}(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

The output of DAEN hidden layer is:

$$h_i = \frac{1}{1 + e^{-(\sum_{j=1}^{N} w_{ij} x_j + b_j)}} \tag{6}$$

where $w_{ij}$ is the connection weight between node $i$ at layer $L$ and node $j$ at layer $L+1$, and $b_j$ is the bias of the hidden layer node $j$.

The most commonly used loss function of AE is the mean square error [31], which is defined as:

$$\mathrm{L}(x, \hat{x}) = \sum_{i=1}^{S} (x - \hat{x})^2 \tag{7}$$

Then the loss function of the proposed DAEN model can be expressed as:

$$J(w, b) = \sum_{i=1}^{S} \left(x^i - \hat{x}^i\right)^2 + rR(w, b) \tag{8}$$

where the first term is the mean square error loss, the second term is the penalty term and $r$ is the sparse penalty factor.

The training process of DAEN consists of unsupervised training and fine-tuning. The process is as follows:

(1) The first stage fused feature $\widetilde{\mathbf{X}}$ is used as the input of the DAEN;
(2) Forward propagation. The hidden layer features of the first AE $h_1$ is used as the input of the second AE for unsupervised training until all hidden layers are trained;
(3) The backpropagation (BP) algorithm [32] is used for supervised fine-tuning to further optimize all the weights and biases;
(4) The last hidden layer feature, $h_n$, of the DAEN is fed into the Softmax classifier;
(5) The classification result is obtained.

*3.3. Rolling Bearing Fault Diagnosis Process Based on the Proposed Method*

Based on the proposed method, the process of the rolling bearing fault diagnosis method is as follows:

(1) Acquisition of rolling bearing vibration data from multiple sensors;
(2) The vibration signal of each sensor is preprocessed with VMD, and the 22 features of the signal are extracted based on the preferred IMF;
(3) The extracted feature is fused into multidomain feature dataset;
(4) The multidomain feature dataset is divided into either a training dataset or a testing dataset, according to the set ratio;
(5) The DAEN model is constructed. The parameters of the DAEN model are initialized, the training dataset is taken as the input to the model and the model loss function is minimized;
(6) The test dataset is fed into the trained DAEN model to obtain the test accuracy.

## 4. Experiment

*4.1. Rolling Bearing Test Bench*

To verify the superiority of the proposed method, the experimental data are obtained from the self-made rolling bearing fault test bench belonging to Anhui University of Technology, as shown in Figure 3. The experimental bearing is 6206-2RS1 SKF. Different depth faults are manufactured on the inner ring, outer ring and rolling ball for the rolling bearing by electric sparkline cutting technology. Figure 4 presents four different health states for rolling bearing.

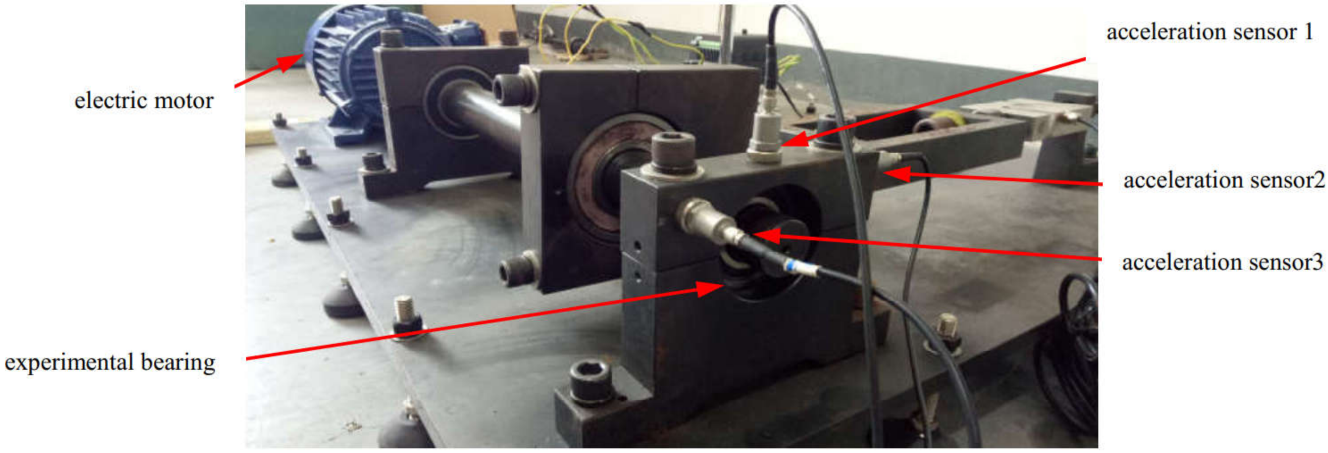



**Figure 3.** Schematic diagram of rolling bearing test rig.


**Figure 4.** Different health states of rolling bearings.

*4.2. Rolling Bearing Multisensor Signals*

The sampling frequency is set to 8192 Hz. When the load is 5 KN and the motor speed is 300 r/min, the signals of the rolling bearings in different health states are collected. Figure 5 shows the time-domain vibration signals of rolling bearings from three different directional sensors. The signals collected from each directional sensor contain six health states, including two types of inner ring faults with the fault depth of 0.3 and 0.4 mm, two types of outer ring faults with the fault depth of 0.2 and 0.3 mm, and one type of rolling bearing normal state.

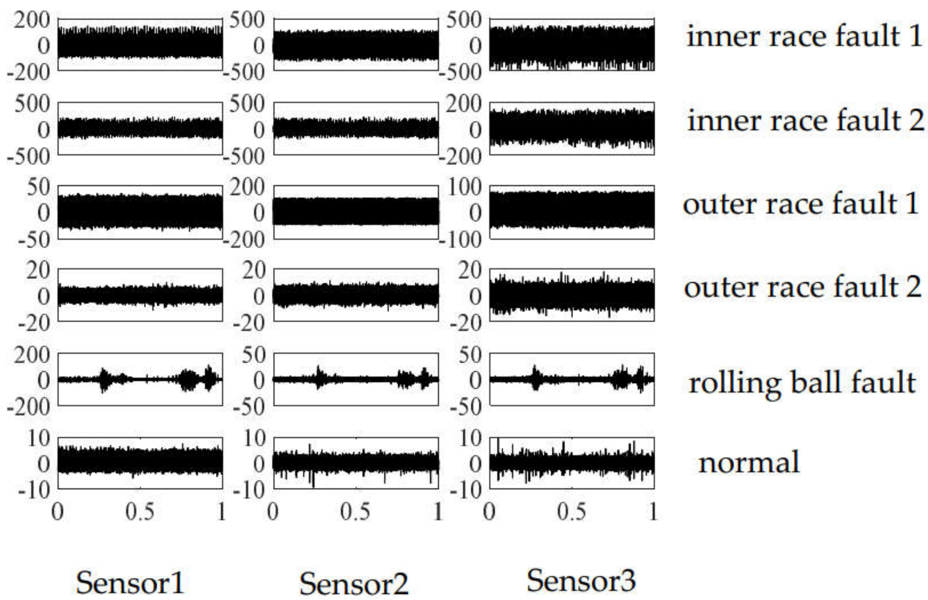



**Figure 5.** Time-domain vibration signals of rolling bearing from three different sensors.

### *4.3. Dataset Construction*

Under the same fault type, 1024 data points are taken as one sample, and 100 samples are taken for each fault type randomly, which comes to 600 samples in total in this experiment. Three IMF components were obtained by decomposing each sample with VMD, and 17 time-domain and frequency-domain features were extracted for each IMF component, as well as five multiscale entropy values. After feature extraction, a sample of 1024 data points is changed into a sample of 66 data points as the input of the proposed model and the comparison model. 90% of them are randomly divided into the training set and 10% into the testing set, as shown in Table 1. That is, each category obtained a training sample of faults with a data dimension of 90 × 66 and a test sample of 10 × 66. After fusion at the one-dimensional feature level, each type of fault of the multisensor signal obtained a training sample of 90 × 198 and a test sample of 10 × 198.

**Table 1.** Bearing dataset information.

| Fault Type | Fault Depth/mm | Size of Training Dataset | Size of Testing Dataset | Label |
|---|---|---|---|---|
| Inner race fault 1 | 0.3 | 90 | 10 | 1 |
| Inner race fault 2 | 0.4 | 90 | 10 | 2 |
| Outer race fault 1 | 0.2 | 90 | 10 | 3 |
| Outer race fault 2 | 0.3 | 90 | 10 | 4 |
| Rolling ball fault | 0.2 | 90 | 10 | 5 |
| Normal | 0 | 90 | 10 | 6 |

### *4.4. Comparative Experiments and Analysis of Results*

#### 4.4.1. The Feasibility and Effectiveness of Multisensor Collaborative Diagnosis

In order to prove the feasibility and effectiveness of multisensor collaborative diagnosis, the vibration signals in three directions of sensor and multisensor fusion signals are input into DAEN for comparison according to the dataset construction method in Section 4.3. Through many experiments, the structure of DAEN based on a single sensor signal is set as [66 50 30 10 6], and the structure of DAEN based on multisensor signals is set as [198 50 30 10 6], i.e., one input layer, three hidden layers and one output layer [30]. The initial learning rate of DAEN is 0.01, the maximum number of iterations is 100, the sparse parameter $r$ is 0.01 and the sparse penalty coefficient is 0.13. In order to eliminate the influence of random errors, 10 experiments were conducted for each method, and the mean and standard deviation of the 10 experimental results were used as the evaluation index of the method. A total of 10 experimental results were compared, as shown in Figure 6, and the mean accuracy and standard deviation of the 10 experiments are shown in Table 2.

As can be seen from Table 2, compared with single sensor 1~sensor 3, the diagnosis accuracy based on multisensor fusion is improved by 4.43%, 10.10% and 6.27%, respectively. The above results show that the diagnosis effect based on multisensor fusion signal is significantly better than that of the single sensor fusion signal, which proves that multisensor signal co-operative diagnosis is feasible and effective. At the same time, we can see from Table 2 that the diagnostic accuracy of different sensors is very different, indicating that the fault information contained in different sensor signals is different. When different sensors co-operate in a diagnosis, more accurate and reliable results can be provided.

#### 4.4.2. Verification of the Superiority of the Proposed Method

To verify the performance of the proposed model, we compared stacked sparse autoencoder (SSAE), traditional machine learning method random forest (RF) and support vector machine (SVM). For fair comparison, the network structure of SSAE is the same as the proposed method, and the sparse parameter in SSAE is set to 0.2 and the sparse penalty coefficient is set to 0.15. The maximum depth of RF is set to 2, which contains 200 trees. The kernel function of SVM adopts RBF function. The penalty factor and kernel function parameters are set to 10 and 0.01, respectively.

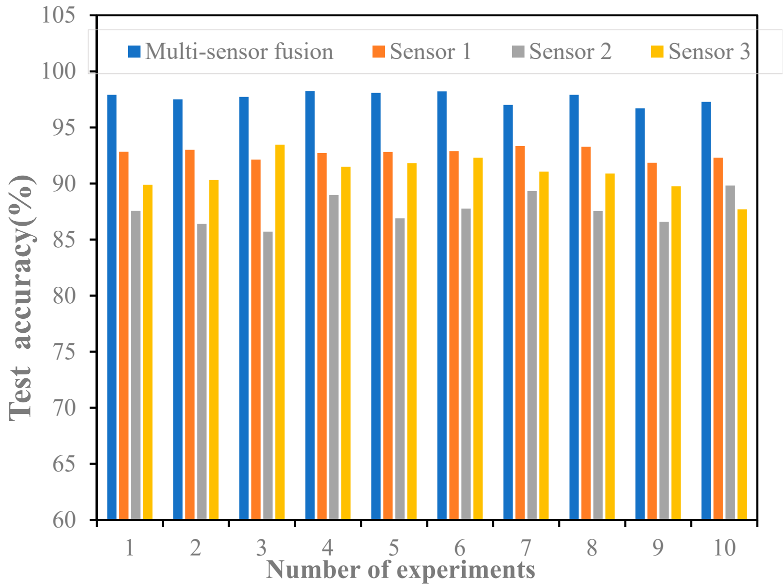



**Figure 6.** Comparison of 10 experiment results for different sensors' datasets.

**Table 2.** The diagnostic result of different sensor dataset.

| Method | Average Test Accuracy (%) | Standard Deviation |
|---|---|---|
| Multisensor fusion (The proposed method) | 97.55 | 0.485 |
| Senor 1 | 93.12 | 0.589 |
| Senor 2 | 87.45 | 1.418 |
| Senor 3 | 91.28 | 1.803 |

In order to eliminate the influence of random errors, 10 experiments were conducted for each method, and the mean and standard deviation of the 10 experimental results were used as the evaluation index of the method. 10 experimental results were compared, as shown in Figure 7, and the mean accuracy and standard deviation of the 10 experiments are shown in Table 3.

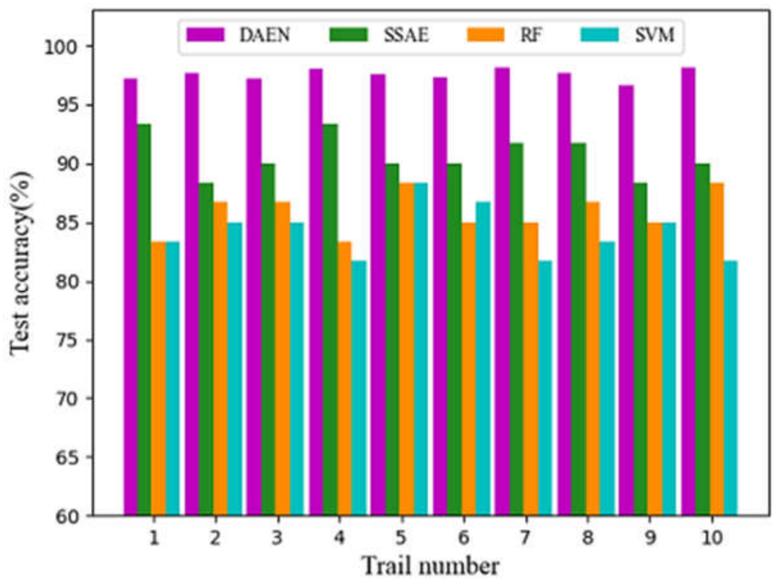



**Figure 7.** Comparison of experimental results.

**Table 3.** The average accuracy and standard deviation.

| Method | Average Test Accuracy(%) | Standard Deviation |
|---|---|---|
| The proposed method | 97.55 | 0.485 |
| SSAE | 90.67 | 1.792 |
| RF | 85.83 | 1.801 |
| SVM | 84.16 | 2.255 |

As can be seen from Figure 7 and Table 3, among the four methods, as traditional machine learning methods, the diagnostic results of RF and SVM in 10 experiments are lower than the other two autoencoder networks. This shows that the traditional machine learning method has a weak feature extraction ability and a low generalization ability when dealing with complex signals, and it is difficult to obtain a good diagnosis effect. Among the two autoencoder networks, the diagnostic accuracy of SSAE is 6.88% lower than that of DAEN, and the standard deviation is increased by 71.26%, which indicates that SSAE has a weaker feature extraction ability. The proposed method has the highest diagnostic accuracy and the lowest standard deviation in 10 experiments, indicating that the proposed method can mine fault-sensitive features effectively, make more, full use of multisensor information and improve the diagnostic effect and stability.

Figure 8 shows the confusion matrix of the first trial of the proposed method. The horizontal co-ordinates of the confusion matrix plot are the true labels, the vertical co-ordinates are the predicted labels and the numbers on the diagonal lines indicate the classification accuracy of the proposed method for each type of sample. From Figure 8, it can be seen that the proposed method can identify 100% of the five conditions of inner ring fault 2, outer ring fault 1, outer ring fault 2, rolling ball failure and normal condition for the rolling bearing dataset of six health conditions. The only misclassification occurred in the inner ring fault 1 sample.

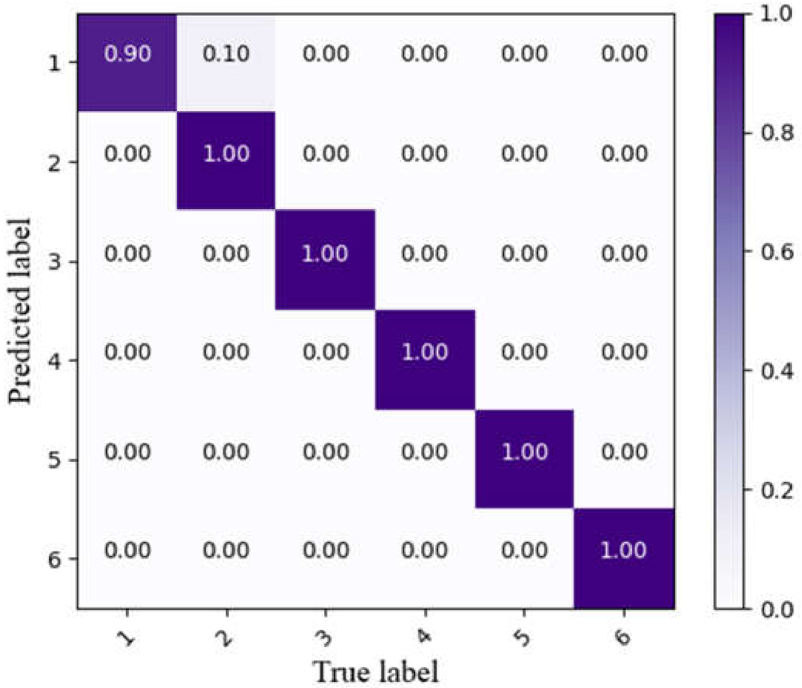
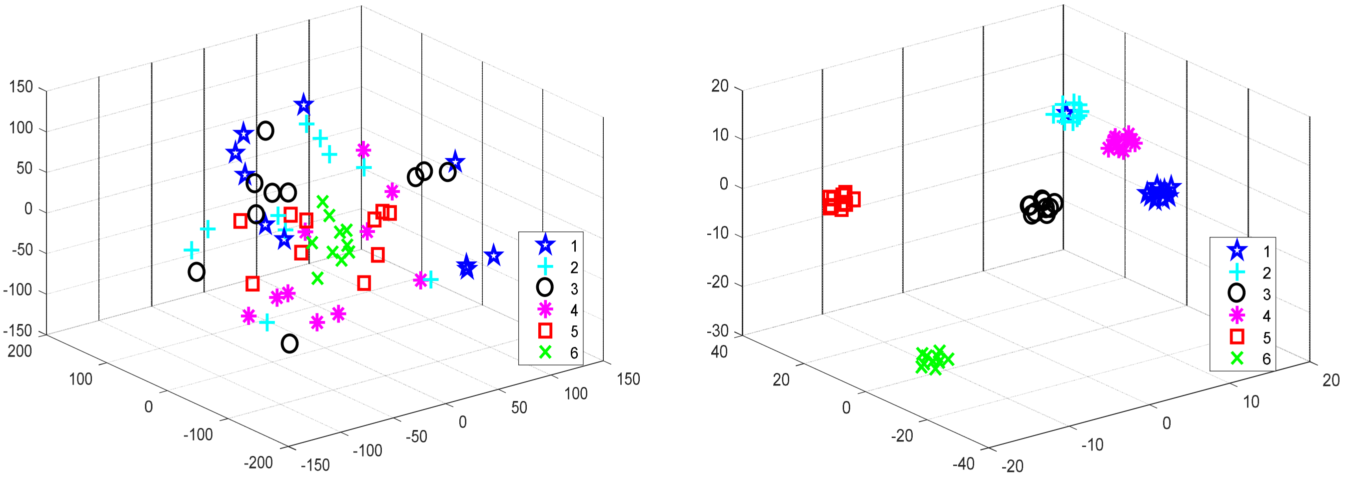



**Figure 8.** Confusion matrix of the first trial of the proposed method.

The t-distribution neighborhood embedding (t-SNE) algorithm [33] is adopted for feature visualization. T-SNE method is used to draw scatter plots of the raw data, respectively. The output of the features from the Softmax layer of the proposed method is shown in Figure 9. From Figure 9, it can be seen that the raw time-domain signal contains too much redundant information, and the features of all categories are difficult to distinguish. In contrast, the features extracted by the proposed method in the Softmax layer are easier to distinguish and show a better classification effect, i.e., the same fault features are clustered according to the same center and different fault features are distinguished, which proves the better performance of the proposed method.




(**a**) (**b**)

**Figure 9.** Feature visualization. (**a**) Feature visualization of raw signal; (**b**) Feature visualization of Softmax layer.

## 5. Conclusions

In order to improve the fault diagnosis accuracy of rolling bearings, a novel multisensor feature fusion method is proposed in this paper. VMD is used to decompose multiple sensor signals, which reduces the redundant information contained in the raw signals. The multidomain features of each single sensor are fused at the feature-level, and the complementary information among multiple sensors is effectively utilized. The depth features of multisensor are further learned and fused with the constructed DAEN. The diagnosis effect of the proposed method is better than that of a single sensor, showing better robustness and providing a more effective means for fault signal deep mining and multisensor information fusion.

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