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Research on Bearing Fault Diagnosis of Wind Turbine Gearbox Based on 1DCNN-PSO-SVM

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ABSTRACT Gearbox bearings play an important role in wind power generation system. Their regular and stable operation will increase wind turbine power generation and improve the economic efficiency of wind farms. They often fail because they work under complex wind conditions. Therefore, it is necessary to find the fault early. The vibration signal of the gearbox bearing has the characteristics of volatility and continuity. Traditional bearing fault diagnosis methods are often based on signal analysis and feature selection, and the process is relatively complex. Deep learning methods can extract and select features automatically, thereby reducing the workload. A fault diagnosis method based on deep learning is proposed in this study. This method combines a one-dimensional convolutional neural network (1DCNN), support vector machine (SVM) classifier, and 1DCNN adaptively extracts features. The extracted features are input into the SVM classifier, and particle swarm optimization (PSO) is used to optimize the SVM classifier. The results show that the proposed fault diagnosis method is effective for fault diagnosis of wind turbine gearbox bearings. This method improves the precision and accuracy of diagnosis when compared to other methods.

INDEX TERMS Wind power, gearbox bearings, deep learning, fault diagnosis.

I. INTRODUCTION

In recent years, renewable energy has become increasingly important. Renewable energy can play a role in protecting the ecological environment and alleviating the use of electrical energy. It has gained more attention all over the world and has been widely produced and utilized. Wind power generation is one of the most thoughtful and promising methods for generating renewable energy. As more wind farms are built, large numbers of wind turbines are put into operation, and related problems also follow. Wind turbines usually operate in places with relatively harsh environments, such as gobi, islands, and grasslands. They are subject to wind impact all year round, the load is extremely unstable, and the temperature difference between day and night is large. Therefore, wind turbines are more prone to failure. The component most likely to fail a wind turbine failure is the gearbox. The gearbox is located at high altitude, and maintenance is extremely difficult if it fails. Over 70% of wind turbine gearbox failures are bearing failures, according to statistics. Gearbox bearings are an important part of wind turbines, and their operating conditions affect the functions of the entire wind turbine equipment to a large extent. It plays a vital role in the process of power transmission. Failure of the gearbox bearings would significantly affect the normal operation of the transmission system. Since gearbox bearings play a key role in wind turbines, if a failure occurs, it is likely to cause major emergencies and huge economic losses, therefore to ensure its safe and stable operation is of great importance. An in-depth study on the fault diagnosis of wind turbine bearings is of great importance for reducing maintenance time, increasing annual power generation, reducing the operating and maintenance costs of wind turbines, and improving the economic benefits of wind farms.

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As a vulnerable part of the wind power system, the functional status of bearings has a huge impact on the performance, stability, and service life of the entire wind power system. Research on bearing fault diagnosis of wind turbines has made some progress today. Researchers have proposed different diagnosis methods for the bearing fault diagnosis of the wind turbine. There are many traditional diagnosis methods based on the classification of "signal processing feature extraction + machine learning", which requires a great deal of signal processing technology and diagnosis experience. Signal processing techniques include fast fourier transform (FFT) [1], empirical mode decomposition (EMD) [2], wavelet transform (WT) [3], broadband mode decomposition (BMD) [4]–[6], etc. In the case of extremely slow bearing speed, Mishra *et al.* [7] used order analysis to process the envelope of short-time angle synchronous averaging signal of wavelet de-noising estimate to diagnose bearing faults. The proposed four-level sequential signal processing method eliminates irrelevant vibration signal components. It avoids the tailing of the signal and only exposes the fault frequency and its harmonics to the frequency spectrum, which has a good diagnosis effect. Georgoulas and Nikolakopoulos [8] proposed a vibration signal feature fusion method for the diagnosis of bearing fault. This method is suitable for a diagnosis system with two accelerometers, the use of a covariance matrix for feature fusion, and the use of principal component analysis anomaly detector, nearest neighbor anomaly detector, and gaussian anomaly detector for fault diagnosis, and then the use majority agreement rules for integration. The authors [9] detect an early fault of single-phase induction motors through sound signals characteristics using the proposed frequency-multi-amplitude selection method for feature extraction, and then uses the Nearest Neighbor classifier (NN), Nearest Mean Classifier (NM) and Gaussian Mixture Models (GMM) to classify for extracted fault features. Experiments show that this method can be used to diagnose faults of single-phase induction motors used in other types of rotating motors. These methods require a great deal of professional knowledge and experience, and it is difficult to exploit the best features from the dynamic environment. Traditional diagnosis methods have not been able to meet the intelligent diagnosis requirements of bearings in wind power generation.

Since 2012, deep learning has entered a period of vigorous development. Today, deep learning methods have been successfully used in computer vision [10]–[15], speech recognition [16]–[21], natural language processing, [22]–[27], and other fields. The outstanding advantage of deep learning compared to the traditional method is that deep learning methods have the potential to automatically extract and select features from data, thereby reducing the workload [28]. As the number of industrial data increases, enough sample data will be provided for deep learning, which means that more knowledge can be discovered automatically. Using traditional machine learning methods to diagnose faults in wind turbine bearings has been unable to meet the actual application needs of wind farms. Current research focuses on the use of deep learning methods in the field of wind turbine fault diagnosis. Shao *et al.* [29] proposed a method to diagnose bearing fault based on a deep belief network. This method uses double complex wavelet packets to preprocess the collected sample data and uses the preprocessed data to train the deep belief network, and finally, the fault is classified by a softmax classifier. Tao *et al.* [30] proposed a bearing fault diagnosis method based on bacterial foraging decisions and deep belief networks. This method uses the collected sample data to train the deep belief network, construct the fitness function of the bacterial foraging decision algorithm, and to measure the pros and cons of the model by calculating the fitness level of each bacterium. Because the bacterial foraging decision algorithm has a parallel search capability, it can effectively select the number of hidden nodes, learning rate, momentum, and other parameters of the deep belief network to generate a suitable classifier to improve the accuracy of carrying bearing fault diagnosis. Long *et al.* [31] proposed a hybrid evolutionary algorithm to optimize the echo state network (ESN) to intelligently diagnose faults, and achieved better results. Sun *et al.* [32] used a deep neural network based on denoising sparse auto-encoder to diagnose the faults in bearings and motors, first trains a layer of denoising reduction sparse auto-encoder to extract features, connects the first two layers of the trained encoder to the last fully connected layer, build a three-layer deep network, and finally use supervised training to update the network weights. Long *et al.* [33] proposed a fault diagnosis technique based on the Sparse Echo Automatic Encoder Network (SEAEN). The diagnostic performance was evaluated in the experiment, and its superiority was proved by comparison with other intelligent fault diagnosis technologies. Zhang *et al.* [34] proposed a deep convolutional neural network with the first layer of wide kernels. This method uses the original vibration signal as input and the wide kernels in the first convolutional layer to extract features and suppress high-frequency noise by using AdaBN to improve the domain adaptability of the model. The performance of this method is better than the new deep neural network (DNN) model based on frequency characteristics under different workloads and noisy environmental conditions. Genders and Razavi [35] for the first time used convolutional neural networks to diagnose the bearings and gears in the gearbox. The network consists of a convolutional layer and a fully connected layer. First, the signal is subjected to a discrete fourier transform to convert the original time-domain vibration signal to a frequency domain, and then the convolutional neural network is directly trained to achieve fault diagnosis. The experimental results show that the feature learning method based on the convolutional neural network is superior to the classical feature engineering method. Lei *et al.* [36] for the first time applied Long Short-Term Memory Network (LSTM) to diagnose a faulty wind turbine and achieved good results. Eren [37] proposed a one-dimensional convolutional neural network (1DCNN) based bearing fault diagnosis, to realize an end-to-end intelligent diagnosis. Huang *et al.* [38] constructed a one-dimensional convolutional neural network (1DCNN), which directly takes

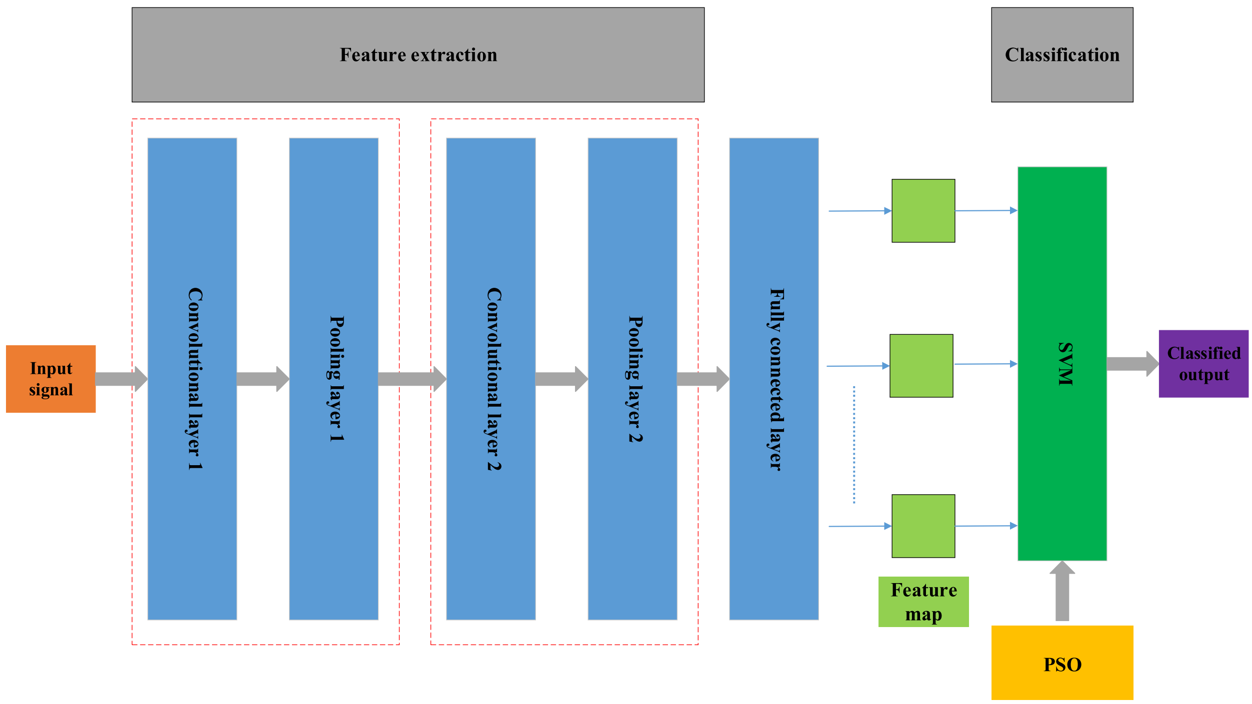


FIGURE 1. Architecture of the proposed 1DCNN-PSO-SVM model.

the vibration signal during mechanical operation as input. It can realize intelligent mechanical fault diagnosis and improve the accuracy of diagnosis and operation efficiency. Shao *et al.* [39] proposes an improved convolutional neural network (CNN) with transfer learning a new framework for fault diagnosis of rotor bearing systems under different working conditions. Although the above fault diagnosis methods can correctly diagnose wind turbine bearing faults in most cases, there is room for further improvement.

A fault diagnosis method based on deep learning is proposed. Our contributions in this article include:

(1) 1DCNN is used to extract the original vibration signal of the gearbox bearing, to adaptively learn the fault features from the original data, and to extract the feature information useful for fault diagnosis.
(2) Use the support vector machine (SVM) classifier to finely identify the extracted fault features.
(3) Optimize the SVM classifier by introducing particle swarm optimization (PSO) algorithm to achieve the best classification effect and make the fault diagnosis more accurate and effective.

The rest of the article is organized as follows. Section II introduces the fault diagnosis method based on 1DCNN-PSO-SVM. Section III introduces related experiments. In Section IV, the experimental results are presented and analyzed and evaluated. Finally, in Section V, conclude and discuss future work.

II. METHODOLOGY

The proposed fault diagnosis model based on 1DCNN-PSO-SVM is shown in Figure 1. The input of the model is the original vibration signal of the wind turbine gearbox bearing, and the output is the result of the fault diagnosis of the wind turbine gearbox bearing. The model composed of 3 main modules: the 1DCNN, PSO and SVM. The 1DCNN module is used to extract information on the characteristic of the vibration signal of the bearing of the wind turbine gearbox, and the SVM classifier module is used for fault classification. The PSO module's function is to optimize the relevant parameters of the SVM classifier and to improve the accuracy and effectiveness of the fault diagnosis. First train the 1DCNN model, use 1DCNN to adaptively extract features related to bearing fault diagnosis, and then input the extracted features into the PSO-SVM classifier for classification. Since the hyperplane learned by SVM is the plane farthest from the sampling point of each category, the generalization ability of SVM is better than the original softmax. Therefore, the features extracted by 1DCNN are input into the SVM classifier for classification. The PSO algorithm is used to train the bearing features input to the SVM classifier to find the best parameters c and g of the SVM classifier, so that SVM can find the best classification decision surface and make the bearing fault diagnosis of the wind turbine gearbox more accurate and effective. The three main modules are described in detail below.

A. 1DCNN

Convolutional neural network (CNN) refers to a neural network that utilizes convolution operations in at least one layer of the network rather than ordinary matrix multiplication operations. Convolution is a special linear operation;

each layer of the convolutional network usually includes three layers: convolutional layer, activation layer, and pooling layer. In the field of image recognition, 2DCNN is generally used to extract features from images. The classic CNN models are: LeNet [40], AlexNet [41], VGG [42], GoogleNet [43], ResNet [44], etc. Since the input gearbox bearing vibration signal is one-dimensional, the one-dimensional convolutional neural network is used to extract the relevant characteristics of the vibration signal of the wind turbine gearbox bearing. The input of a one-dimensional convolutional neural network is one-dimensional data, so its convolution kernel also adopts a one-dimensional structure. The output of each convolutional layer, activation layer, and pooling layer also corresponds to a one-dimensional feature vector. The basic architecture of 1DCNN will be introduced in this section.

1) CONVOLUTIONAL LAYER

The convolution layer performs convolution operation on the one-dimensional input signal and the one-dimensional convolution kernel and then extracts local features through the activation layer. The vibration signal of the wind turbine gearbox bearing is input to the convolutional layer of the one-dimensional convolutional neural network to perform the convolution operation. The convolution process is shown in formula (1).

$$x_k^l = \sum_{i=1}^{n} conv(w_{ik}^{l-1}, s_i^{l-1}) + b_k^i \tag{1}$$

In the formula: x_k^l, b_k^l respectively represent the output and offset of the k-th neuron in layer l; s_i^{l-1} represent the output of the i-th neuron in layer l-1; w_{ik}^{l-1} represents the convolution kernel of the i-th neuron in layer l-1 and the k-th neuron in layer l, $i = 1, 2, \ldots, n$, n is the number of neurons.

2) ACTIVE LAYER

The activation layer performs a nonlinear transformation on the input signal through a nonlinear function to enhance the expressive power of the convolutional neural network. Currently, the most common activation functions are Sigmoid, Tanh, and Relu. Because the Relu function converges quickly and can overcome the gradient dispersion, it is widely used. Therefore, the Relu function is used as the activation function, and its formula is shown in (2).

$$y_k^l = f(x_k^l) = \max\{0, x_k^l\} \tag{2}$$

In the formula, y_k^l is the activation value of layer l.

3) POOLING LAYER

The pooling layer is usually applied after the convolutional layer. Downsampling reduces the spatial size of the network features and parameters, reduces the amount of calculation, and prevents overfitting. The vibration signal features of the wind turbine gearbox bearing, which is extracted through the convolution layer and the activation layer, are introduced into the pooling layer to simplify the features, retain useful features, reduce the unnecessary features, and make the extracted features more reflective of the wind turbine gearbox bearing. Common pooling operations are average Pooling and maximum Pooling. In this study, the pooling layer uses maximum pooling this time and the formula is shown in (3).

$$z_k^{l(j)} = \max_{(j-1)r+1 \le t \le jr} \{y_k^{l(t)}\} \tag{3}$$

In the formula, $z_k^{l(j)}$ represents the jth value in the k-th neuron of layer l after pooling operation; $y_k^{l(t)}$ represents the t-th activation value in the k-th neuron of layer l; r is the width of the pooling area. The hyperparameters settings of the 1DCNN module are shown in Table 1.

TABLE 1. 1DCNN model parameter hyperparameters.

number of layers	structure types	hyperparameters
1	Convolutional layer 1	The size of the convolution kernel is 3, the number of convolution kernel channels is 1, and the number of convolution kernels is 8.
2	Pooling layer 1	Pooling block size is 2.
3	Convolutional layer 2	The size of the convolution kernel is 3, the number of convolution kernel channels is 1, and the number of convolution kernels is 16.
4	Pooling layer 2	Pooling block size is 2.
5	Fully connected layer	The number of nodes is 512.

B. SVM

The main idea of support vector machine (SVM) [45] is to create an optimal decision hyperplane to maximize the distance between the two forms of samples closest to the plane on both sides of the plane, and a strong generalization capability. In the case of a non-linear separable pattern classification problem, the non-linear projection of the complex pattern classification problem is projected into a high-dimensional feature space, and the non-linear classification problem is transformed into a linear classification problem in the high-dimensional space. The hyperplane equation used by SVM for classification is shown in formula (4).

$$\boldsymbol{W}^T \boldsymbol{X} + b = 0 \tag{4}$$

In the formula, $\boldsymbol{X}$ is the input vector; $\boldsymbol{W}$ is the weight vector; b is the offset.

According to the principle of structural risk minimization, the cost function of the weight value $\boldsymbol{W}$ and the relaxation variable ε_i is shown in formula (5).

$$f(\boldsymbol{W}, \varepsilon_i) = \frac{1}{2}\boldsymbol{W}^T \boldsymbol{W} + c\sum_{i=1}^{i} \varepsilon_i \tag{5}$$

In the formula, c is the punishment factor, which controls the degree of punishment for the wrongly divided samples. ε_i is the relaxation variable, which measures the deviation of a data point from the linearly separable ideal condition.

The radial basis function (RBF) is selected as the kernel function this time, which satisfies the mapping to the high-dimensional space to obtain the optimal hyperplane. The formula is shown in equation (6).

$$K(x, x_i) = \exp[-\frac{\|x - x_i\|^2}{\sigma^2}] = \exp[-g\,\|x - x_i\|^2] \quad (6)$$

In the formula, $g = \frac{1}{\sigma^2}$, the value of g determines the number of new support vectors in the feature space and affects the speed of training and classification.

The input of the SVM classifier is the output of the one-dimensional convolutional neural network, that is, the feature information of the wind turbine gearbox bearing extracted after the one-dimensional convolutional neural network. The key to the success of the SVM classifier is the setting of the penalty parameter c and the kernel function parameter g. g represents the influence of a single training sample on the whole. The larger the value of g the smaller the influence of the individual, but too large the value of g the greater the over-fitting of the sample; conversely, the smaller the value of g, the greater the influence of the individual on the overall size of the sample. However, if the value of g is too small, the sample individuals pay too much attention to them and may ignore the complexity of the sample as a whole. As the penalty parameter, c is used to balance misclassified samples and smoothness of the interface. Generally, the smaller the value of c, the smoother the interface; and as the value of c increases, the degree of freedom of selection increases, which will allow more samples to be correctly classified. The selection of c and g is thus very important. The traditional SVM needs to artificially set the values of c and g according to experience. To ensure that the SVM achieves better classification results and higher adaptability, particle swarm optimization (PSO) algorithm is proposed to optimize the traditional SVM, to find the optimal parameter solution, and to make the classification results of wind turbine gearbox bearing faults more accurate.

C. PSO

Particle Swarm Optimization (PSO) [46] is an intelligent swarm global search algorithm based on the iterative model proposed by Kennedy and Eberhart in 1995. The principle of PSO is to treat the parameters to be optimized in n-dimensional space as a group of random particles, each particle has a certain speed to determine the direction and distance they travel. The particles have a memory function that can remember the current position and the current optimal position. The particle swarm is continuously modified by the optimal solution found by itself and the optimal solution currently found by the population until the optimal solution is found for the entire population. Each particle updates its speed and position according to formula (7) and formula (8) and searches through generations until the optimal solution is obtained.

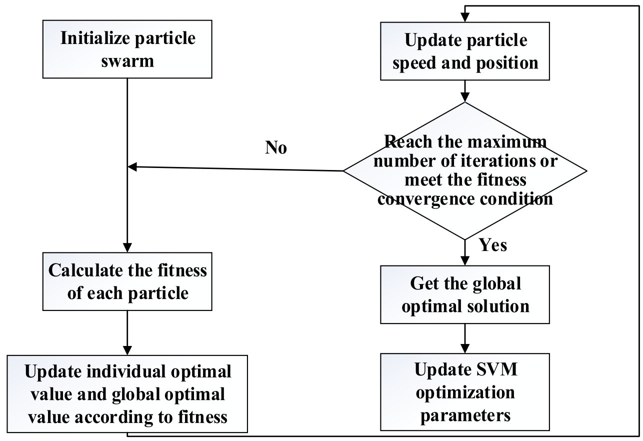


FIGURE 2. PSO flow chart.

$$\begin{aligned} V_i(k+1) &= \omega V_i(k) + C_1 r_1 (P_{\text{best}} - x_i(k)) \\ &\quad + C_2 r_2 (g_{\text{best}} - x_i(k)) \qquad (7) \\ x_i(k+1) &= x_i(k) + kV_i(k+1) \qquad (8) \end{aligned}$$

where ω is the weighting factor; C_1 and C_2 are the learning factors; r_1 and r_2 are any numbers evenly distributed between the intervals [0, 1]; P_{best} is the best position currently found by the individual particle; g_{best} is the current best position found by the particle population. The flow chart of PSO is shown in Figure 2.

The PSO principle is simple, easy to implement, and not too many parameters have to be manually modified. Iterative optimization can only be performed by specifying the particle swarm size and parameter optimization interval. The PSO algorithm is used to train the characteristics of the wind turbine gearbox bearing input to the SVM classifier to find the optimal parameters of the SVM classifier so that the SVM can find the optimal hyperplane classification, and the bearing fault diagnosis of the wind turbine gearbox is more accurate and effective.

III. EXPERIMENT

A. THE DATASET

Because the vibration signal of the gearbox bearing fault of the wind turbine is difficult to collect, the experimental data comes from the bearing data center of Case Western Reserve University (CWRU). The CWRU data acquisition system is shown in Figure 3.

As shown in Figure 3, the bearing data collection platform consists of a 2 hp motor (left), a torque sensor/encoder (center), and a dynamometer (right). The test bearing supports the motor shaft. The research object of this experiment is the driving end bearing in the picture, and the faulty bearing is of the empirical dynamic modeling (EDM). There are three kinds of fault locations for the diagnosed bearings, which are rolling element faults, outer ring faults, and inner ring faults. The fault diameters include 0.007inch, 0.014inch, and

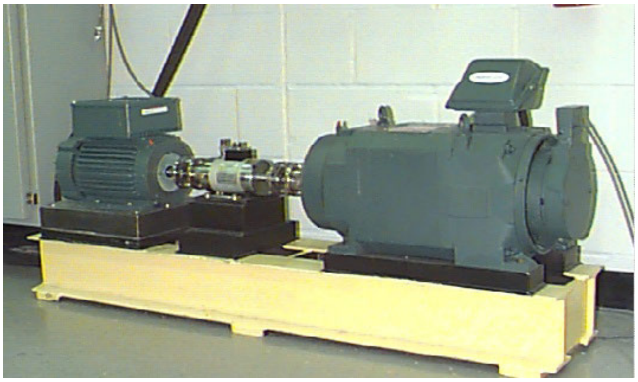


FIGURE 3. Bearing data acquisition platform.

TABLE 2. Description of bearing dataset.

Fault Labels	Fault Location	Fault Diameter(inch)
0	None	None
1	Ball	0.007
2	Ball	0.014
3	Ball	0.021
4	Outer Race	0.007
5	Outer Race	0.014
6	Outer Race	0.021
7	Inner Race	0.007
8	Inner Race	0.014
9	Inner Race	0.021

0.021inch, a total of 9 fault states. There are 10 types of bearing status plus the normal state. The CWRU data acquisition uses an acceleration sensor. The acceleration sensor is placed on the drive end. The acceleration sensor is used to collect the bearing vibration signal. The sampling frequency is 48 kHz. The 10 types of bearings are shown in Table 2.

B. EXPERIMENTAL DESCRIPTION

1) DATA PREPROCESSING

The first thing in the experiment is to preprocess the original vibration signal to generate the data set required by the model, which is convenient for training and testing the model. Therefore, data preprocessing is very important. 70% of the original bearing vibration signal data is used as the training set, 20% is used as the verification set, and the remaining 10% is used as the test set. The data set is generated by sliding through a sliding window with a displacement of 28 steps with a size of 864 points. The training set, verification set, and test set are generated by sliding through sliding windows of the same size without overlapping. The pre-processed data set has 10 different categories, and each category contains 1000 data.

2) MODEL PARAMETER SETTING

The structure of the proposed bearing fault diagnosis model for wind turbine gearbox is shown in Figure 1. Among all the parameters, the 1DCNN module is used to extracting the relevant characteristic information of the bearing fault of the wind turbine gearbox. The specific network structure of this module is shown in Table 3.

TABLE 3. The layers of the network and the main attributes.

Layer	Output Shape	Parameters
conv1d_1	(None, 864, 8)	32
activation_1	(None, 864, 8)	0
max_pooling1d_1	(None, 432, 8)	0
conv1d_2	(None,432, 16)	400
activation_2	(None, 432, 16)	0
max_pooling1d_2	(None, 216, 16)	0
flatten_1	(None, 3456)	0
dropout_1	(None, 3456)	0
dense_1	(None, 512)	1769984

In Table 3, the first column represents the network structure name of each layer in 1DCNN. The second column indicates the size of the feature vector output by each layer of the 1DCNN. The third column indicates the number of parameters that need to be trained for each layer of 1DCNN. The input of conv1d_1 layer is the wind turbine gearbox bearing data after preprocessing of the data. The output of the dense_1 layer is the relevant feature information of the wind turbine gearbox bearing extracted by the 1DCNN module after convolution, activation, and pooling, and the extracted feature information is then sent to the PSO-SVM classifier for failure classification. The loss function of this model is the cross-entropy loss function, and the formula (9) of this function is shown below.

$$loss = -\sum_{i=0}^{9} y_i \log(p_i) \tag{9}$$

From the above equation, y_i is the actual label value of the wind turbine gearbox bearing fault, p_i is the output of the neural network, and i is the category of the wind turbine gearbox bearing.

The SVM module uses the RBF kernel function in this model, and the key parameters c and g are obtained by PSO algorithm optimization. The parameters C1 and C2 of the PSO algorithm are set to 0.9, the population number is set to 10, and the parameter optimization interval is [0, 20]. The PSO algorithm is used to optimize the SVM classifier to make bearing fault diagnosis of wind turbine gearbox more accurate and effective.

3) EVALUATION STANDARD

Commonly used wind turbine gearbox bearings fault diagnosis evaluation indicators include Precision (P), Recall(R), Accuracy (Acc), and F1 score (F1). The Accuracy and F1 score are used to measure the overall performance of the model. The higher the index, the stronger the fault diagnosis capability of the model, and the better the overall performance. Precision is used for prediction samples, and calculate how many of the predicted samples are correctly predicted. The Recall is based on the original actual samples, how many are correctly predicted. The fitness function of PSO is the accuracy of bearing fault diagnosis of wind turbine gearbox. The formulas for these four evaluation indicators are

TABLE 4. Comparison of optimizer effects.

optimizers	Acc(%)	P(%)	R(%)	F1(%)
SGD	48.3	75.0	48.0	48.0
RMSprop	86.3	92.0	86.0	87.0
Adagrad	92.0	94.0	92.0	92.0
Adadelta	88.8	93.0	89.0	88.0
Adam	98.2	98.0	98.0	98.0

as follows:

$$P = \frac{TP}{TP + FP} \tag{10}$$

$$R = \frac{TP}{TP + FN} \tag{11}$$

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

$$F1 = 2^* \frac{P^* R}{P + R} \tag{13}$$

In the formula, TP is true positive, which means that the true category of the sample is a positive example, and the expected result of the model is also a positive example. FP is a false positive, which means that the true category of the sample is a negative example, but the model predicts it as a positive example. FN is a false negative, which means that the true category of the sample is a positive example, but the model predicts it as a negative example. TN is a true negative, which means that the true category of the sample is negative, and the model predicts it as a negative.

IV. RESULTS AND ANALYSIS

The choice of optimizers is one of the key links in the field of deep learning. Different optimizers have different gradient update rules. Even if the same data set and model architecture are used, it would likely lead to different training results with different optimizers. Therefore, it is necessary to choose an appropriate optimizer in the model for the bearing fault diagnosis of the wind turbine gearbox. Currently, there are mainly five different types of optimizers for deep learning model training, which are SGD, RMSprop, Adagrad, Adadelta, Adam, etc. Below, these five different optimizers are used to train the proposed bearing fault diagnosis model of the wind turbine gearbox. The experimental results obtained are shown in Table 4.

In Table 4, Acc, P, R, and F1 represent the Accuracy, Precision, Recall, and F1 score of the test set, respectively. Table 4 shows that the SGD optimizer has the worst effect. Using the SGD optimizer to train the proposed model, the accuracy obtained is 48.3%, and the F1 score is 48.0%. The effect of the RMSprop optimizer has been greatly improved compared to the SGD optimizer. Using the RMSprop optimizer to train the proposed model, the accuracy obtained is 86.3%, and the F1 score is 87.0%. The Adagrad optimizer has a small improvement compared to the RMSprop optimizer; the accuracy reaches 92.0%, and the F1 score reaches 92.0%. The effects of Adadelta and RMSprop optimizers are not very different. The optimization effect of Adam optimizer on the proposed model is the most significant. The accuracy of the model reaches 98.2%, the precision is 98.0%, the recall is 98.0%, and the F1 score reaches 98.0%. The Adam optimizer is therefore used to train the proposed bearing fault diagnosis model of the wind turbine gearbox so that the bearing fault diagnosis of the wind turbine gearbox will be more accurate and effective.

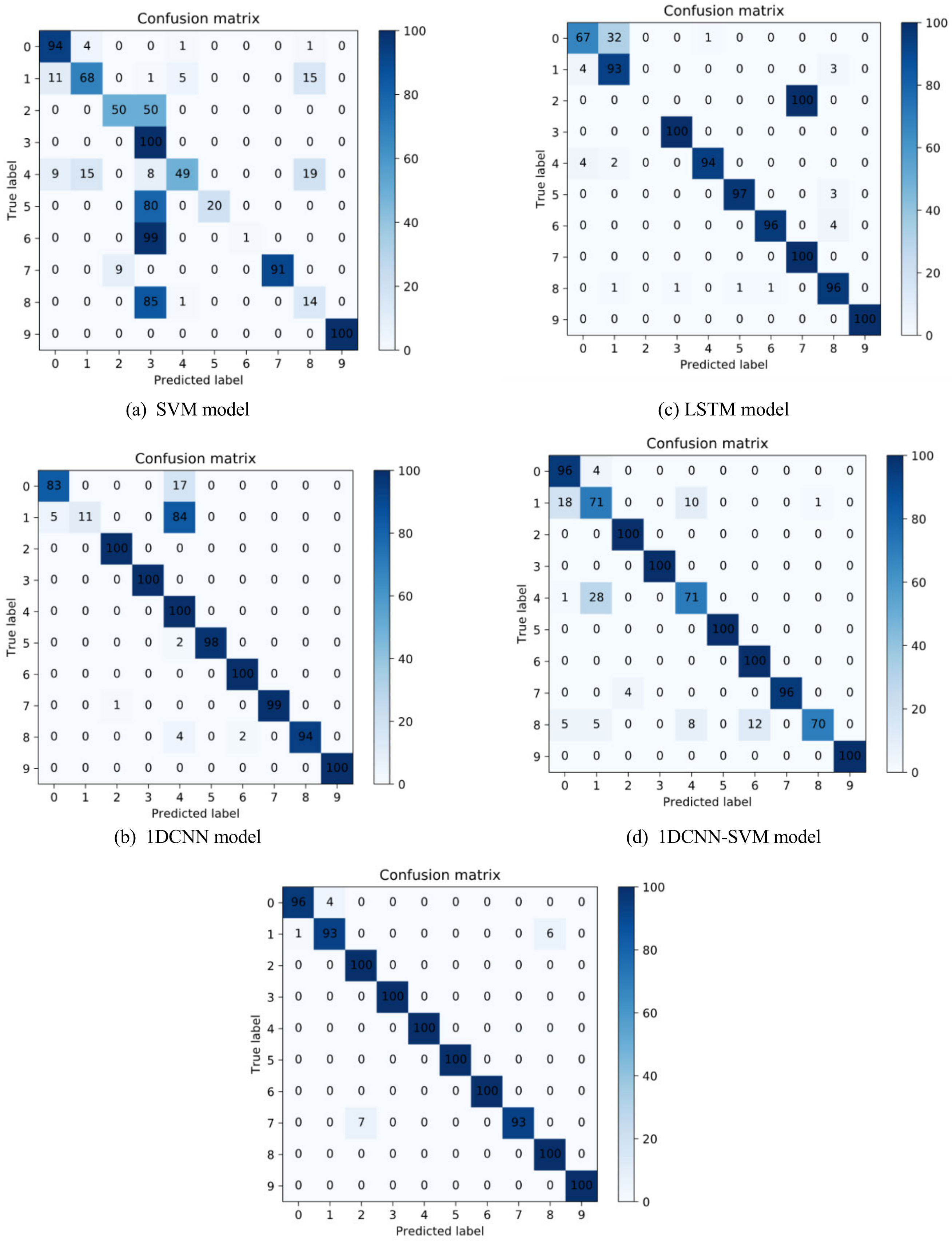
TABLE 5. Comparison of different models.

Model	Acc(%)	P(%)	R(%)	F1(%)
SVM	58.7	79.0	59.0	57.0
1DCNN	88.5	93.0	89.0	85.0
LSTM	85.6	88.0	86.0	85.0
1DCNN-SVM	90.4	91.0	90.0	90.0
1DCNN-PSO-SVM	98.2	98.0	98.0	98.0

The experiment compared the SVM model, 1DCNN model, LSTM model, 1DCNN-SVM model, and the proposed model. The parameter settings of the SVM model, 1DCNN model, and 1DCNN-SVM model are the same as the proposed model and the size of batch processing batch_size=128. The number of neurons in the LSTM model is set to 32. The values of 4 evaluation indicators of the 5 different models are shown in Table 5. They are Accuracy, Precision, Recall, and F1 score.

Table 5 shows that the diagnostic accuracy of the proposed model is better in these five models than in the other four models. The accuracy of the SVM model, 1DCNN model, and LSTM model are lower than 90.0%, and the accuracy rate of the 1DCNN-SVM model is 90.4%. The proposed model's accuracy is much higher than the SVM model's accuracy, which is 39.5% higher than the SVM model, reaching 98.2%. Therefore, the proposed model has the best fault diagnosis effect from the accuracy evaluation index and is superior to the other four models. From the perspective of precision, only the 1DCNN-SVM model and the proposed model have a precision of more than 90.0%. The proposed model has the highest precision of 98.0%. Regarding the recall, only the proposed model exceeded 90.0%, reaching a recall of 98.0%. The F1 score is used to measure the overall performance of the model. Compared to other models, the F1 score of the proposed model is the highest, reaching 98.0%, indicating that the model has the best overall performance. In summary, the proposed model performs best on the four evaluation indicators of accuracy, precision, recall, and F1 score, indicating that the proposed model has strong fault diagnosis capabilities and good overall performance. It is better to diagnosis the bearing fault of the wind turbine gearbox so that the clean energy of wind power can better serve human beings.

The confusion matrix of the SVM model, 1DCNN model, LSTM model, 1DCNN-SVM model, and the proposed model are shown in Figure 4.



(a) SVM model

(c) LSTM model

(b) 1DCNN model

(d) 1DCNN-SVM model

(e) 1DCNN-PSO-SVM model

FIGURE 4. Confusion matrix of different models.

In Figure 4, the abscissa axis of the confusion matrix represents the predicted category label of the wind turbine gearbox bearing states, and the coordinate axis represents the actual category label of the wind turbine gearbox bearing states. The coordinate values 0-9 for the horizontal axis and the vertical axis respectively represent 10 different types of wind turbine gearbox bearings. Each type has 100 test samples, that is, a total of 1000 test samples in the test set. The value on the left diagonal of the confusion matrix represents the number of samples that the model predicts correctly for each type of wind turbine gearbox bearing states. The larger the value, the more effective the model is in classifying the bearing faults of the wind turbine gearbox. Figure 4 shows that the fault diagnosis effect of the proposed model in wind turbine gearbox bearings is better compared to the SVM model, 1DCNN model, LSTM model, and 1DCNN-SVM model.

V. CONCLUSION

Energy shortage and environmental problems are becoming more prominent. As a clean and renewable energy source, wind power generation has attracted great attention from all over the world. Wind power has played an increasingly important role in the power system. With the continuous increase in the number of wind farms, the troubleshooting of wind power installations has become an important issue that needs to be addressed urgently. In recent years, bearing fault diagnosis of wind turbines has become the focus of common concern in the industry and the development of new energy.

A fault diagnosis method for the bearing of wind turbine gearbox based on 1DCNN-PSO-SVM is proposed in the study. One-dimensional bearing vibration signal is input to 1DCNN for feature extraction, and feature information useful for the fault diagnosis is extracted. The extracted features then input into the PSO-SVM classifier for fault diagnosis. The role of PSO among others is to optimize the relevant parameters of the SVM classifier so that the bearing fault diagnosis of the wind turbine gearbox would be more accurate and effective.

This method is used to diagnose faults in wind turbine bearing and compared to other intelligent diagnosis methods. The results confirm that the proposed method does not require any manual feature extraction and signal processing operations of the original data during the entire diagnosis process, eliminates the dependence on manual feature extraction, and can overcome the limitations of traditional methods based on expert experience. Experimental results show that this method is more effective than other existing of intelligent diagnosis with SVM, 1DCNN, LSTM, and 1DCNN-SVM. Additionally, our approach in this study can be easily extended to other large industrial fault diagnoses. The author will continue to study related issues in this direction in the future.

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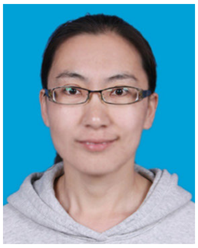

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