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Fault monitoring and diagnosis of motorized spindle in five-axis Machining Center based on CNN-SVM-PSO

Shuo WANG[1], Zhenliang YU[1*], Xu LIU[2], Zhipeng LYU[3]

1. School of Mechanical and Power Engineering, Yingkou Institute of Technology , Yingkou, China
2. Yingkou Dingsheng Heavy Industry Machinery Co. LTD, Yingkou, China
3. School of Mechanical and Power Engineering, Shenyang University of Chemical Technology , Shenyang, China

***Corresponding Author:** yuzhenliang, email address: yuzhenliang_neu@163.com*

Abstract:
A spindle fault diagnosis method based on CNN-SVM optimized by particle swarm algorithm (PSO) is proposed to address the problems of high failure rate of electric spindles of high precision CNC machine tools, while manual fault diagnosis is a tedious task and low efficiency. The model uses a convolutional neural network (CNN) model as a deep feature miner and a support vector machine (SVM) as a fault state classifier. Taking the electric spindle of a five-axis machining centre as the experimental research object, the model classifies and predicts four labelled states: normal state of the electric spindle, loose state of the rotating shaft and coupling, eccentric state of the motor air gap and damaged state of the bearing and rolling body, while introducing a particle swarm algorithm (PSO) is introduced to optimize the hyperparameters in the model to improve the prediction effect. The results show that the proposed hybrid PSO-CNN-SVM model is able to monitor and diagnose the electric spindle failure of a 5-axis machining centre with an accuracy of 99.33%. In comparison with the BP model, SVM model, CNN model and CNN-SVM model, the accuracy of the model increased by 10%, 6%, 4% and 2% respectively, which shows that the fault diagnosis model proposed in the paper can monitor the operation status of the electric spindle more effectively and diagnose the type of electric spindle fault, so as to improve the maintenance strategy.
Keywords: *five-axis machining centres; CNN-SVM; spindle vibration; fault diagnosis*

1 Introduction

Five-axis machining centre is a high technology, high efficiency, low energy consumption in one of the high-precision machine tools, widely used in the complex space surface processing, its core key components failure of intelligent identification to enhance the overall level of equipment maintenance technology is of great significance. The electric spindle is directly driven by an electric motor instead of a pulley drive and gear drive, which can achieve high-speed and steady-state operation of the machine tool spindle, and is a key functional component of the five-axis machining centre, whose working condition directly affects the spindle rotation accuracy and product processing quality[1]. It is a key functional component of a five-axis machining centre. Therefore, effective monitoring and accurate diagnosis of spindle faults is essential. Monitoring means timely warning when a spindle fault occurs, and diagnosis means intelligent identification of the type of fault for accurate maintenance at a later stage. Fault detection and diagnosis models are used to monitor and mine the vibration signals of each fault in the spindle and to construct a non-linear correlation with the actual fault. In the early days, a large number of scholars used machine learning methods to build prediction models for intelligent maintenance of motorized spindle, such as BP neural networks [2],RBF neural networks[3], Support vector machines (SVM)[4] etc.

Li Zhaolong [2] et al. collected temperature and axial thermal drift data of electric spindles at different rotational speeds, used fuzzy clustering and grey correlation analysis for feature extraction, and constructed a BAS-BP model to predict and compensate for the thermal errors of electric spindles, achieving better results. Shan Wentao [3] et al. proposed a block adaptive backstepping control method based on global RBF neural network. The backstepping control law and parameter update law were derived using Lyapunov theory to ensure the stability of the whole spindle system. C.K. Madhusudana [4] et al. collected vibration signals in the feed direction of the spindle in the healthy and faulty states of the milling cutter and used SVM models with different kernel functions to investigate and classify

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selected features based on the discrete wavelet transform, and the results showed that spindle faults could be effectively diagnosed using this C- SVC model. Although the above-mentioned scholars have made some achievements using mechanical learning algorithms, the slow model fitting speed and low prediction accuracy have become urgent problems at this stage.

With the application of sensor technology and the rise of deep learning algorithms, has become a new trend to use piezoelectric acceleration sensors to acquire electric spindle vibration signals and construct fault diagnosis models for monitoring by deep learning algorithms, such as recurrent neural networks (RNN) [5], long and short term memory networks (LSTM) [6] and Convolutional Neural Networks (CNN) [7] etc. These predictive models have more powerful feature learning and mapping capabilities and can automatically mine deeper features for prediction without a priori knowledge or the help of human experts. However, recurrent neural networks (RNN) are prone to gradient disappearance or gradient explosion when diagnosing spindle faults, and researchers have used Long and Short Term Memory Networks (LSTM) to predict spindle faults [8]. Convolutional neural networks (CNNs) have been used for spindle fault monitoring and diagnosis in recent years because their convolution and pooling operations can improve the extraction of potential features in the hidden layer of the prediction model compared to LSTMs.

Wen Long[9] et al. proposed a CNN convolutional neural network for electric spindle bearing fault diagnosis, which can effectively perform fault monitoring, but there is still room to improve the accuracy of diagnosing specific fault types. This is due to the fact that when using a CNN diagnostic model to deal with functions with a high degree of non-linearity, the number of features output by the fully connected layer increases proportionally, reducing the generalisation capability of the model, which is not conducive to fault diagnosis of electric spindles. Support vector machines (SVMs), on the other hand, have an absolute advantage in dealing with non-linear data by using some kernel function to transform the input sample data from a low-dimensional space into a high-dimensional space, so that the originally non-linear data becomes linearly separable in the high-dimensional space[10] It uses a kernel function to transform the input sample data from a low-dimensional space to a high-dimensional space, so that the originally non-linear data becomes linearly separable in the high-dimensional space. Therefore, the combination of SVM and CNN can make up for the shortcomings of the above CNN model. The essence is that CNN is used as a feature learner to explore the deep features of the input data, and SVM is used as a trainer to construct the optimal classification hyperplane for fault classification prediction.

CNN-SVM is a multi-category diagnostic model proposed by combining convolutional neural network (CNN) and support vector machine (SVM) methods. Its model performance depends on the selection of model parameters, which include penalty parameters ρ and kernel function width g, etc., and it is crucial to select the optimal parameter pairing to further improve the model performance. The current more common hyperparameter optimisation methods are random optimisation search [11] , gradient-based optimisation[12], genetic algorithm optimisation[13], Particle swarm optimization[14]et al. The PSO algorithm can perform global optimization with fewer parameters, and its powerful search performance and individual optimization capability can accelerate the convergence speed of the model, so it has been widely used and studied by scholars in recent years [15] .This is why it has been widely studied in recent years.

In this paper, a hybrid CNN-SVM model based on particle swarm algorithm (PSO) optimisation is proposed. Firstly, the fully connected layer of the CNN model is replaced by a global average pooling layer to reduce the dimensionality of the output features and improve the generalisation capability of the model; secondly, the Softmax function of the CNN model is replaced by a support vector machine SVM classifier to complete the fault diagnosis of the electric spindle; finally, the hyperparameters in the SVM model are optimised using the PSO algorithm to derive the optimal solution to further improve the Finally, the PSO algorithm is used to optimise the hyperparameters in the SVM model and derive the optimal solution to further improve the fault diagnosis accuracy of electric spindles.

2 Construction of a CNN-SVM-PSO fault diagnosis method

To address the shortcomings of the CNN diagnosis model, this paper proposes a fault diagnosis model based on a CNN-SVM optimised by a particle swarm algorithm to identify the types of faults in the electric spindle system of a 5-axis machining centre. The improvements are:

(1) The sample feature matrix is pre-processed using batch normalisation techniques and then input into the CNN model, which reduces the complexity of the model and improves the convergence speed of the network with its unique structure of local connectivity and weight sharing.

(2) The fully connected layer of the CNN model is replaced by a global average pooling layer, and the features output after the convolution and pooling operations are reduced in dimensionality, which reduces the model parameters and lowers the training time of the SVM model.

(3) The SVM model is suitable for classification tasks dealing with problems with high non-linearity and makes up for the shortcomings of the CNN model, so the SVM model is used instead of the Softmax classifier in the CNN to classify and predict the electric spindle fault types, thus improving the model generalisation capability.

(4) Using the powerful search and global optimization-seeking capabilities of the PSO algorithm, the penalty parameter in the SVM modelρ and the two

parameters of kernel function width g are iteratively optimized to improve the accuracy of electric spindle fault diagnosis. The CNN-SVM-PSO fault diagnosis model is shown in Figure 1.

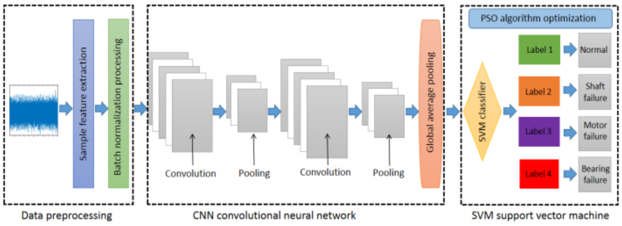


Figure 1 CNN-SVM-PSO fault diagnosis model

2.1 Acquisition of electric spindle vibration signals

During the operation of a five-axis machining centre, the electric spindle system will generate violent vibrations when problems occur in the core components such as the rotating shaft, motor and bearings, which are manifested by the loose and unbalanced phenomenon of the rotating shaft and coupling, the eccentric phenomenon of the air gap of the motor, as well as the damage failure of the bearings and rolling bodies. By monitoring the vibration of the machine tool spindle system when the above core components are abnormal, it is found that the frequency range of the vibration signals of various faults are slightly different, as shown in Table 1, so the spindle fault can be diagnosed by extracting the features of each fault vibration signal and finding the correlation between the sample features and the actual fault[16].The sample features can then be correlated with the actual fault to diagnose the spindle fault.

Table 1 Frequency range of core component failures

Electric spindles Type of fault	Frequency range	Type of vibration
Unbalanced and loose rotating shafts and couplings	5 times Within working frequency	Low frequency vibration
Motor air gap eccentricity failure	2x Power frequency	Medium Frequency Vibration
Bearings and rolling elements Injuries	＞1KHz	High frequency vibration

The vibration information generated by the electric spindle system of the five-axis machining centre due to the above faults will be reflected in different ways, such as irregular fluctuations of the spindle motor current, the vibration of the outer casing of the spindle and the noise generated by the electric spindle system. The experiment is to use the 356A15 three-axis vibration acceleration sensor manufactured by PCB to monitor and collect the vibration signal generated by the outer casing of the spindle in real time under the high-speed rotating state of the electric spindle, the Measuring system models is shown in Figure 2, the Experimental equipment model parameters is shown in Table 2.

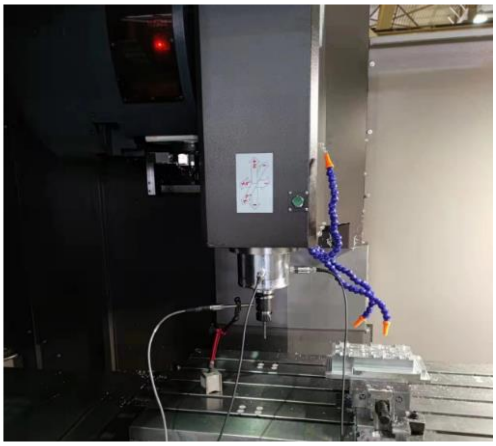


Figure 2 Measuring system models

Table 2 Experimental equipment model parameters

Serial number	Experimental equipment	Model parameters
1	Five-axis machining centres	SK5L-70100 i5M8
2	Acceleration sensors	PCB, Type 356A15
3	Data Acquisition Cards	NI-DAQ, 50HZ
4	Output Connector	BNC interface

In this paper, the raw vibration signals of the electric spindle system are collected in real time according to the above scheme. A total of four tag states are collected: normal (set as tag 1), spindle fault (set as tag 2), motor fault (set as tag 3) and bearing fault (set as tag 4). The number of samples collected for each of the four tag states is 100, giving a total of 400 data. As the raw signal data set collected contains 3 channels of X-axis, Y-axis and Z-axis vibration signals, a raw signal matrix of 400 x 3 is formed.

2.2 Electric spindle fault feature extraction

The instability of the five-axis machining centre electric spindle system at the moment of start/stop can interfere with the signal feature extraction, so the original signal needs to be processed for noise reduction. This experiment each acquisition signal data volume is about 200000 or more, so extract each acquisition signal in the label for 50001 ～ 100000 data for research, in order to avoid the interference of the noise signal, to the normal state of the data set as an example, its noise reduction signal results are shown in Figure 3.

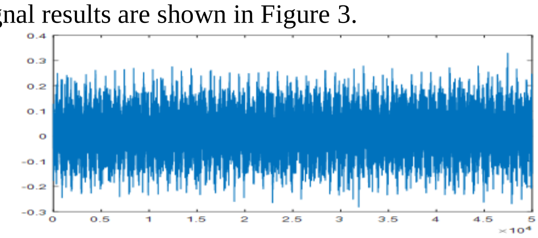


Figure 3 Spindle vibration signal data after noise reduction

After noise reduction, the original vibration signal is extracted in the time domain, frequency domain and time-frequency domain. 13 time-domain features are extracted in total, including mean value, variance, cliff index, peak factor, etc.; 5 frequency-domain features are extracted, including frequency-domain amplitude mean value, mean square frequency, variance frequency, etc.; the time-frequency domain features are extracted mainly by using wavelet packet analysis to subdivide the original signal into different frequency bands, and the energy value of each frequency band is the extracted time-frequency domain features. The energy value of each frequency band corresponds to the type of electric spindle fault, so the energy value of the frequency band is the extracted time-frequency domain features, and the energy value of the frequency band is calculated by the formula:

$$E_n\left(x(t)\right) = \frac{1}{2^{-k}N-1}\sum_{m-0}^{2^k-1}\left(x^{k,m}(i)\right)^2 \quad (1)$$

where En denotes the total energy of the original signal, j denotes the number of layers of wavelet packet decomposition, and$x^{k,m}(i)$ denotes the number of layers in the subspace $U_{j-k}^{2^k+m}$ of the signal x_{2^k+m} of the decomposed signal. In this experiment, the number of layers of wavelet packet decomposition of the original signal is set to 3, which are all done by the db5 wavelet base. The frequency domain is divided into 8 frequency bands, as shown in Figure 4, so that 8 time-frequency domain features are extracted. Therefore, 26 features can be extracted for each channel signal. The features of all channels are fused to produce 78 eigenvalues and the matrix is reorganised to produce a 400 x 78 eigenmatrix, which is the input to the electric spindle fault diagnosis model.

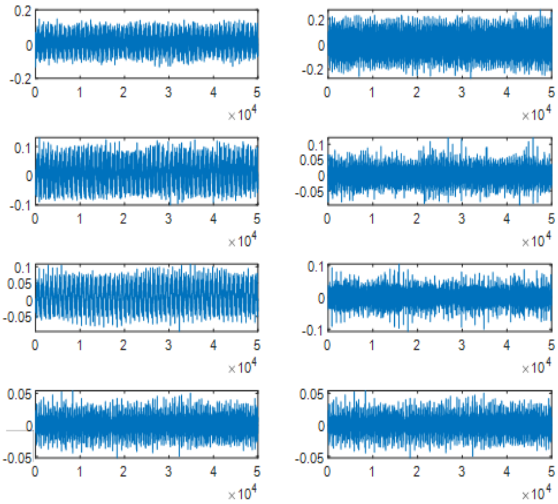


Figure 4 Frequency bands for wavelet packet decomposition

2.3 Fault diagnosis principle of CNN-SVM-PSO model

Firstly, the 400 x 78 sample feature matrix is reorganised using the batch normalisation technique; secondly, the sample data is input into the CNN model and passed into the global average pooling layer for feature dimensionality reduction after two successive convolution and pooling operations; finally, the reduced dimensional feature vector is passed into the SVM model optimised by the PSO algorithm for electric spindle fault diagnosis. The specific fault diagnosis principle is as follows:

According to the above, the 400×78 sample feature matrix was derived from the feature extraction of the original vibration signals of the four labels in the time domain, frequency domain and time-frequency domain, and the above feature matrix was batch normalized to avoid the occurrence of overfitting due to gradient dispersion, and the processing formula for batch normalization was

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (2)$$

where X denotes the sample for each feature, andX_{min} denotes the minimum value of each feature, andX_{max} denotes the maximum value of each feature.

The sample information is indirectly characterized by the weight value of each layer derived from the convolution operation, the higher the layer, the more detailed the local features are extracted, and the spatial continuity of the sample is maintained[17] .The convolution operation is given by

$$X_i^k = \sum_{j=1}^{n} W_i^{kj} \otimes X_{i-1}^{j} + b_i^k \quad (3)$$

where X_i^k denotes the feature matrix of the kth neuron at the output of the ith layer, andW_i^{kj} denotes the weight value of the kth neuron at layer i, and$\otimes$ denotes the convolution operator, andX_{i-1}^{j} denotes the feature matrix of the jth neuron at the output of layer i-1, andb_i^k is the bias coefficient of the kth neuron in layer i.

In order to improve the fault diagnosis performance of the prediction model, the CNN model uses ReLU function for non-linear activation, which has good non-saturation characteristics and avoids the gradient disappearance phenomenon. The activation function is as follows:

$$V_i^k = Relu\left(X_i^k\right) = \begin{cases} 0, x_i^k < 0 \\ x_i^k, x_i^k > 0 \end{cases} \quad (4)$$

Where x_i^k is the value of theX_i^k the respective eigenvalues in the feature matrix.

The pooling type is chosen to be maximum pooling, which preserves the original features and reduces the parameters of network training, improving the robustness of the extracted features. The maximum pooling formula is:

$$C_i^k(s,t) = \underset{\substack{1+(s-1)Q \le d \le sQ \\ 1+(t-1)P \le h \le tP}}{Max}\left\{V_i^k(d,h)\right\} \quad (5)$$

where$V_i^k(d,h)$ is the eigenvalue of column h of row d of the ith eigenmatrix input to the pooling layer, and$C_i^k(s,t)$ is the eigenvalue of the sth row t column of the ith feature matrix obtained after pooling, and P and Q are the length and width of the pooled region, respectively.

The feature matrices of dimension S × T, which are derived from each row of the 400 × 78 sample feature matrix after two convolution and pooling operations, are fed into the global average pooling layer. The dimensionality of the pooling kernel of the global average pooling layer is kept consistent with the dimensionality of the feature matrix, and the n feature matrices are dimensionalized to output a feature vector Xr = {x1 , x2 , ... , xi , ... , xn , }, where xi is given by the formula

$$x_i = \frac{1}{ST}\sum_{s=1}^{S}\sum_{t=1}^{T} C_i^k(s,t) \tag{6}$$

The feature vector output from the global average pooling layer is used as input to the SVM support vector machine model. The greatest advantage of the SVM algorithm is that the number of features in a dataset has essentially no effect on its model complexity, making it particularly suitable for classification tasks with relatively large datasets of features, and the mathematical model of the SVM is

$$\begin{cases} min\ \frac{1}{2}\|w\| + \rho\sum_{r=1}^{L}\xi_r \\ s.t. y_r(wX_r + b) + \xi_r \geq 1, r = 1,2, \cdots, L \end{cases} \tag{7}$$

where w is the normal vector to the hyperplane, and ρ is the penalty parameter, the ξ_r is the relaxation factor, b is the offset coefficient, and X_r is the feature vector of the rth sample, the y_r is the fault class, L is the total number of feature samples, and the total number of samples in this paper is 400.

The model in Eq. (7) is mostly used to deal with linearly divisible sample characteristics data, but the electric spindle fault sample data is linearly indivisible, so it is necessary to introduce the kernel function to up-dimension each labeled sample data. In this paper, the Gaussian radial basis kernel function is used to transform the non-linear data of each labeled state into linear data in high dimensional space to make the analysis possible, and then the optimal classification hyperplane is constructed based on the principle of maximizing the classification interval to complete the fault diagnosis task, and its Gaussian radial basis kernel function formula is

$$K(X) = sgn\left(\sum_{r=1}^{L} a_r^* y_r exp\left(-\frac{\|X_r - X\|^2}{2g^2}\right) + \theta^*\right) \tag{8}$$

where sgn is the sign function, a_r^* is the Lagrangian multiplier, g is the kernel function width, and X is the sample label data, and θ^* is the configuration factor.

The five-axis machining centre spindle fault diagnosis has a total of four label states, in essence a multi-classification problem. In the fault diagnosis of the sample, each classifier scores the four label states and the label with the highest score is the final result of the fault diagnosis. The penalty parameter ρ and kernel function width g directly affect the training speed and prediction accuracy of the model, so how to find the optimal ρ , g parameter pairing is the key to SVM model classification prediction [18]. This paper uses the PSO algorithm to perform the SVM classification prediction. In this paper, the PSO algorithm is used to optimise the hyperparameters in the SVM model to derive the optimal solution, and its PSO algorithm optimisation search process is shown in Figure 5.

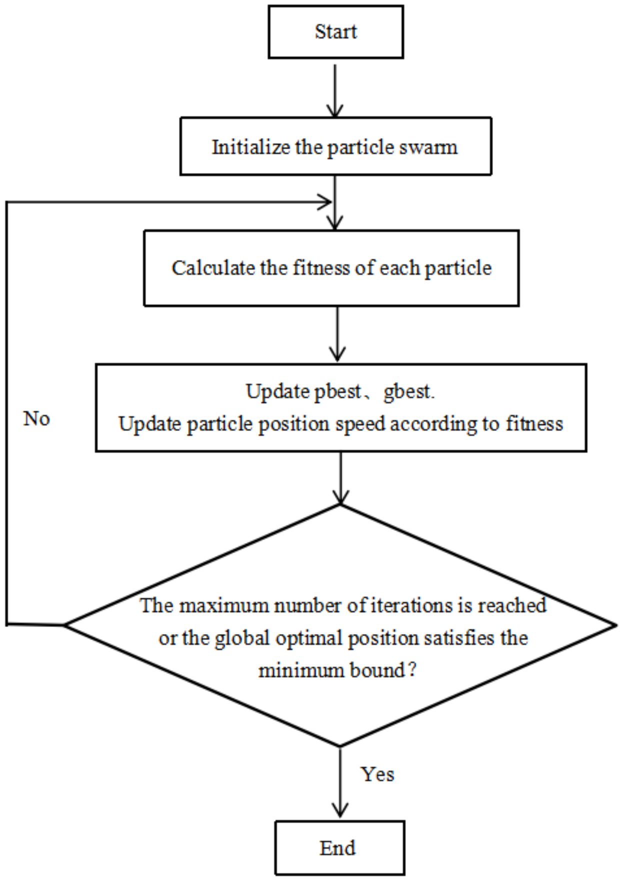


Figure 5 PSO algorithm optimisation process

2.4 Fault diagnosis process with CNN-SVM-PSO model

The process of electric spindle fault diagnosis based on CNN-SVM-PSO model mainly includes the following six stages: sample feature extraction, division of data set, training CNN model, training SVM model, optimization of model parameters and fault type diagnosis. The basic process is shown in Figure 6:

(1) Sample feature extraction: The original signals of the 3 channels related to the electric spindle vibration are extracted in the time domain, frequency domain and time-frequency domain respectively to form a sample feature matrix.

(2) Division of data set: The above sample matrix is normalized, the processed feature parameters are the model input, the four label states of the electric spindle are the model output, and the training data set and the test data set are randomly divided, with the ratio of training data set to test data set being 5:3.

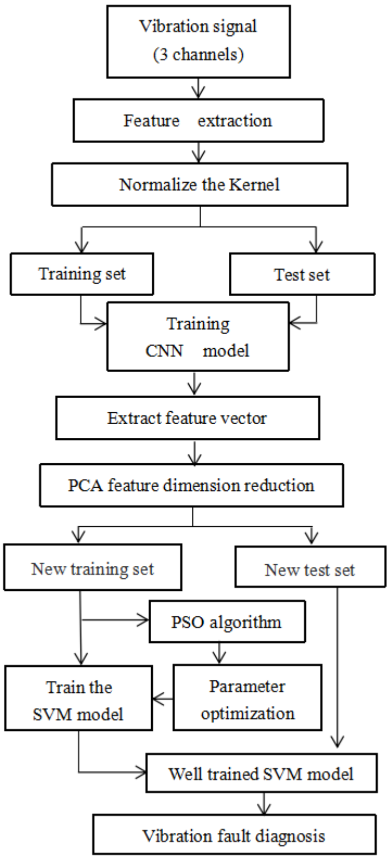


Figure 6 CNN-SVM-PSO fault diagnosis flowchart

(3) Training the CNN model: build a convolutional neural network and train it using the training and test sets from step 2. After two convolutional and pooling operations reduce the training time of the SVM by globally averaging one feature vector output from the pooling layer to form a new training and test set;

(4) Training the SVM model: train the SVM model with the training set formed in step 3, select the Gaussian radial basis kernel function as the basis function of the SVM classifier, initialize the penalty parametersρ and kernel function width g.

(5) Model parameter optimization: Iterative optimization of the hyperparameters of the SVM model based on the training data set using the PSO algorithm to find the optimal c and g parameter pairing to improve the training speed and prediction accuracy of the model

(6) Fault type diagnosis: The test set formed with step 3 is input to the trained SVM model to identify the data fault type and provide a reference for electric spindle fault repair and troubleshooting.

3 Experimental analysis of electric spindle fault diagnosis

3.1 Setting of diagnostic model parameters

In this experiment, a 400×78 sample feature matrix was generated after feature extraction, corresponding to four labeled states, namely normal state (label 1), spindle fault (label 2), motor fault (label 3) and bearing fault (label 4). The CNN-SVM-PSO model was constructed by randomly disrupting the feature matrix and then batch normalising it to construct a training set and a test set, of which the number of training sets was 250 and the number of test sets was 150.ρ and the kernel function width g, both of which were set between 0 and 5, were selected as the target of the optimization process. To avoid interference from other factors, the number of particle swarm individuals in the PSO algorithm was set to 15 and the maximum number of iterations was set to 150, with the specific parameters shown in Table 3. Fifteen optimisation operations were carried out according to the parameters in Table 3, and the average value was taken as the final result, where the penalty parameterρ was 0.401 and the kernel function width g was 1.215. The optimizedρ , g parameters were migrated to the CNN-SVM model to complete the four label fault diagnosis.

Table 3 Initial parameter settings for the PSO algorithm

PSO algorithm parameters	Parameter values
Number of individuals in the particle population	15
Maximum number of iterations	150
Acceleration factors c1, c2	1.3, 1.5
Inertia factor	0.5
Particle vector dimension	2

3.2 Selection of diagnostic model evaluation indicators

In order to quantify the results of electric spindle fault diagnosis, this paper selects Precision, Accuracy, Recall and F1-score values as the evaluation indexes[19]The formulae for the calculation of Precision, Accuracy, Recall and F1-score are as follows

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

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

$$F1 - score = \frac{2TP}{2TP + FP + FN} \tag{12}$$

In the above equation, the values of TP, TN, FP and FN can all be found in the confusion matrix, which is shown in Table 4 for the dichotomy example.

Table 4 Confusion matrix

		True value	
		Normal	Fault
Predicted value	Normal	TP	FP
	Fault	FN	TN

3.3 Electric spindle fault diagnosis results

This experiment takes the electric spindle of a five-axis machining centre as the research object, and uses the acceleration sensor to detect the vibration signals of four label states in real time, and forms the sample data after feature extraction, normalised and input to the CNN-SVM-PSO fault diagnosis model for fault identification, and the fault identification results of the training set obtained are shown in Figure 7, and it can be found that only 1 sample out of 250 training samples, The fault identification results of the test samples are shown in Figure 8, and it can be found that only 1 sample out of 150 test samples was diagnosed incorrectly, with an accuracy rate of 99.33%. The results show that the CNN-SVM-PSO model has a good effect in the diagnosis of electric spindle faults.

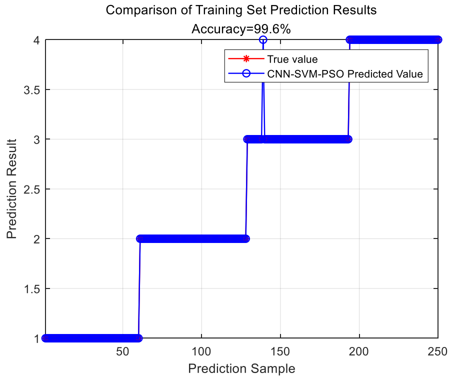


Figure 7 Training set spindle fault prediction results

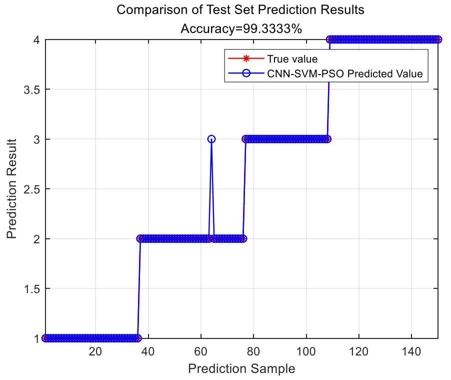


Figure 8 Test set spindle failure prediction results

The confusion matrix of the CNN-SVM-PSO model electric spindle fault diagnosis test set is shown in Figure 9. It can be seen that the test set contains 36 samples of normal state (label 1), spindle fault (label 2) 40, motor fault (label 3) 32 and bearing fault (label 4) 42, total 150 samples. In the diagnosis of the spindle fault (tag 2), one sample was incorrectly classified as a motor fault (tag 3), with an accuracy rate of 97.5%; no errors were found in the diagnosis of normal condition (tag 1), motor fault (tag 3) and bearing fault (tag 4), with an accuracy rate of 100%.

The evaluation index of electric spindle fault diagnosis can be calculated through the confusion matrix, and the results of the evaluation index of its four state labels are shown in Table 5. For the accuracy rate index, it can be seen that the accuracy rate of the spindle fault is the lowest, but it also reaches 97.5%, and all other states can reach 100%, which achieves a better result; for the correct rate index, it can be seen that the accuracy rate of all three wear states is 99.33%, which is consistent with the previous analysis; for the recall rate index, it can be seen that only the recall rate of the motor fault (label 3) does not reach For the F1 value metric, it can be seen that the minimum value of F1 for the four fault types is 0.985, which is close to 1. These four results further validate the superiority of the CNN-SVM-PSO model in the diagnosis of electric spindle faults.

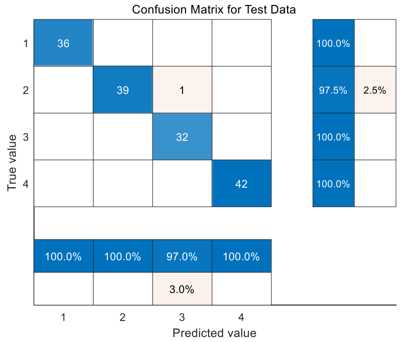
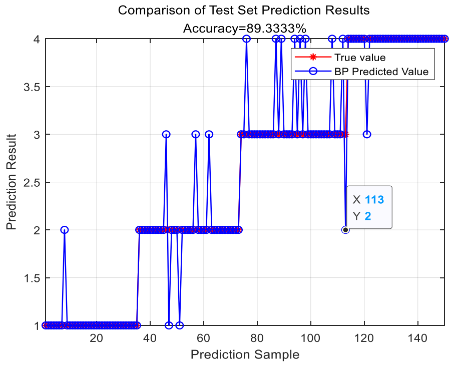


Figure 9 Fault diagnosis confusion matrix

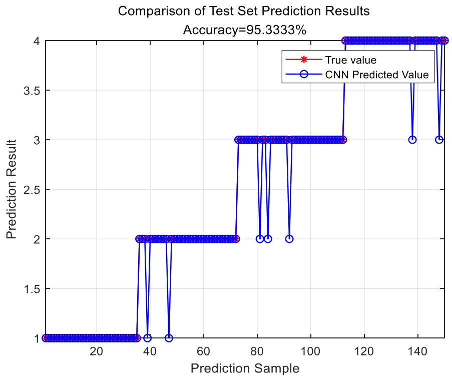
Table 5 Results of the four fault diagnosis evaluations

Label Classification	Precision	Accuracy	Recall rate	F1 value
1	100%	99.33%	100%	1
2	97.5%	99.33%	100%	0.987
3	100%	99.33%	97%	0.985
4	100%	99.33%	100%	1

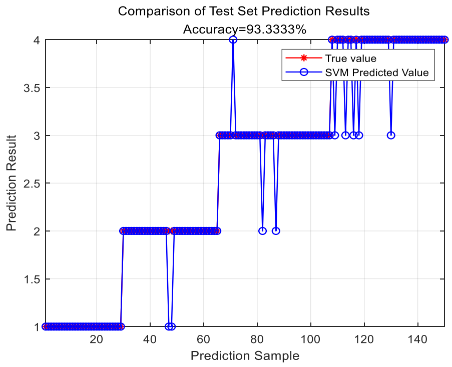
In order to further verify the identification effect of the CNN-SVM-PSO electric spindle fault diagnosis model, the prediction effect was compared with other traditional fault diagnosis models in the past, such as BP neural network, CNN model, SVM model and CNN-SVM model, and the prediction results of these four traditional electric spindle fault diagnosis models are shown in Figure 10. From Fig. 8 and Fig. 10, it can be seen that the prediction effects of the five electric spindle fault diagnosis models are ranked as CNN-SVM-PSO ＞ CNN-SVM ＞ CNN ＞ SVM ＞ BP. It can thus be seen that the hybrid CNN-SVM model based on the optimization of PSO algorithm proposed in this paper has obvious advantages in electric spindle fault diagnosis, which is due to the ability in the CNN-SVM-PSO model to deep mining of data hidden layer features with high nonlinearity and comprehensive feature extraction, and the PSO algorithm is able to perform a deep mining of the penalty parameter in the SVM support vector machineρ The PSO algorithm is able to find the optimal pairing of two hyperparameters in the SVM support vector machine and the kernel function width g, which avoids the blindness of setting parameters and thus improves the accuracy of the prediction model. It is calculated that the CNN-SVM model optimized based on the PSO algorithm improves the accuracy by 2% over the traditional CNN-SVM model.



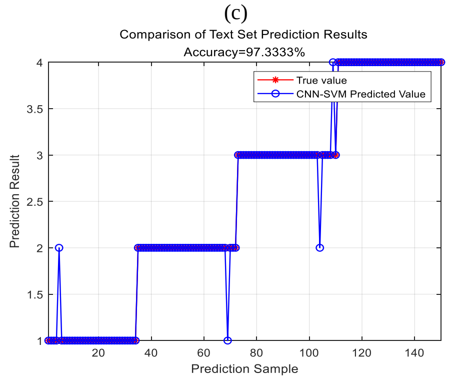
(a)



(b)



(c)



(d)

Figure 10 Prediction results of the four traditional models

(a) BP model. (b) CNN model. (c) SVM model. (d) CNN-SVM model

Table 6 shows the performance comparison results of the five electric spindle fault diagnosis models. The number of diagnostic error samples of BP model, SVM model, CNN model and CNN-SVM model are 16, 10, 7 and 4 respectively, and their accuracy rates are 89.33%, 93.33%, 95.33% and 97.33% respectively. In contrast, the CNN-SVM-PSO model proposed in this paper diagnosed only one wrong sample and the accuracy rate was as high as 99.33%, which improved the accuracy index by 10%, 6%, 4% and 2% respectively compared with the above four traditional models. This shows that under the conditions of consistent samples and the same number of samples, the prediction accuracy of the hybrid CNN-SVM model based on the optimised PSO algorithm for electric spindle fault diagnosis is significantly higher than the other models, and its generalisation ability is stronger and the network fitting speed is faster, which indirectly indicates that using the CNN-SVM-PSO model for electric spindle fault diagnosis is more accurate and can provide a reference for electric spindle fault repair and troubleshooting. This indirectly indicates that the CNN-SVM-PSO model is more accurate for electric spindle fault diagnosis and can provide a reference for electric spindle fault repair and troubleshooting.

Table 6 Performance comparison results of the five diagnostic models

Algorithm	Number of misidentified samples				Accuracy
	Normal Status	Bearing failures	Spindle failure	Motor failure	
BP Neural Network	1	5	9	1	89%
SVM Algorithms	0	2	3	5	93%
CNN Algorithms	0	2	3	2	95%
CNN-SVM algorithm	1	1	2	0	97%
CNN-SVM-PSO algorithm	0	1	0	0	99%

4 Conclusion

In this paper, a CNN-SVM fault diagnosis model based on PSO algorithm optimisation is proposed to classify and predict four labeled states: normal state, spindle fault, motor fault and bearing fault of an electric spindle, taking the electric spindle of a five-axis machining centre as the experimental object. The model uses a convolutional neural network (CNN) model as a deep feature miner and a support vector machine (SVM) as a fault state classifier to complete the diagnosis of electric spindle fault types. In order to improve the prediction accuracy of the model, the powerful search capability of the particle swarm algorithm (PSO) is used to search for the superparameters in the model. The results show that:

(1) The best hyperparameter pairing for the CNN-SVM electric spindle fault diagnosis model was found by the PSO algorithm, where the penalty parameterρ is 0.401 and the kernel function width g is

1.215, which reduces the subjective influence of manual parameter selection and avoids the blindness of setting parameters, thus improving the diagnostic accuracy.

(2) The CNN-SVM-PSO model can effectively monitor and diagnose the common types of faults in electric spindle systems, and its diagnostic accuracy reaches 99.33%.

(3) Under the same conditions, the diagnostic performance of the CNN-SVM-PSO model proposed in this paper was compared with the BP model, CNN model, SVM model and CNN-SVM model, and the results showed that the model constructed in the paper has obvious advantages in electric spindle fault diagnosis, and its accuracy indexes were improved by 10%, 6%, 4% and 2% respectively.

In the future, this CNN-SVM-PSO electric spindle fault diagnosis model can be widely used in the fields of spindle fault diagnosis and intelligent operation and maintenance of CNC machine tools in various factories. By monitoring the vibration signal of the electric spindle in real time, it is of practical significance to achieve early warning and display the type of fault when the vibration signal is abnormal, providing reference advice to maintenance personnel and improving maintenance efficiency.

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