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Identification Method of Vibration Drilling Bit Wear State Based on Signal Imaging and Deep Learning

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In vibration-assisted drilling, the wear state of the drill bit affects the processing quality of the hole. The traditional method of identifying the wear state of the drill bit adopts the method of packet decomposition, ignoring the timing characteristics of the signal. In this paper, the force and acoustic emission signals in vibration-assisted drilling are used. The Gram angle field converts the one-dimensional time series into a two-dimensional image, while retaining the trajectory of the time series in the high-dimensional space. Based on the Graham difference field (GADF) image of force and AE, the Inception improved convolutional neural network (IN-CNN) is used to identify the wear state. The experiment proves that compared with the traditional convolutional neural network, BP neural network and support vector machine, the recognition rate of IN-CNN drill wear state based on GADF is 93.1 %, which is increased by 2.5 %, 10.6 % and 8.1 % respectively. It provides a reliable condition monitoring method for the state identification of the drill bit in semi-closed vibration-assisted machining, and has practical engineering significance for improving the machining accuracy and efficiency of composite equal-holes.

Keywords: vibration-assisted drilling; state recognition; convolutional neural network; gram angle field

1 Introduction

Ultrasonic vibration assisted drilling can optimize the chip removal and chip breaking ability in the machining process, improve the machining quality and improve the service life of the drill bit [1]. Vibration assisted drilling is suitable for the processing of composite materials, deep holes and other holes, but the processing is a semi-closed state, and the state of the drill can not be directly monitored or observed. Therefore, it is of great significance to study the wear state identification of the vibration drilling drill.

Carbon fiber reinforced polymer (CFRP) has the advantages of fatigue resistance, high temperature resistance and friction resistance. It is widely used in shipbuilding, automobile manufacturing and aerospace fields by using laminated materials with matrix metal. However, due to the differences in the nature of the materials, when drilling with the traditional drilling process, the surface of the processed workpiece is prone to defects such as burrs, tears and delamination, which cannot meet the requirements of high precision. Small holes can be manufactured by many conventional and unconventional methods, including laser processing, electrical discharge machining, electron beam drilling, electrochemical machining, electromechanical machining and ultrasonic vibration assisted drilling [2,3]. Through the experimental study on the micro-drilling accuracy of carbon fiber reinforced polymer materials, many scholars have solved the accuracy and delamination problems of CFRP micro-hole processing in the assembly process [4,5,6].

Deep learning is an important branch of machine learning, which can deeply mine the data features in information and find the correlation between information. In 2020, Wang Wenhao proposed a research on drill wear monitoring technology based on GA-LVQ network, which realized the prediction of tool wear and verified the validity of the model [7]. In 2020, Soufiane et al. used continuous wavelet transform to decompose the acoustic emission signal, and input the node energy of the coefficient as the relevant feature into the improved extreme learning machine algorithm to realize the tool wear monitoring [8]. In 2021, Dong et al. identified disc cutter faults based on a multi-scale feature extraction method combining spectral wavelet transform and improved random forest. Experiments show that the identification accuracy can reach more than 90 % under various working conditions and environmental noise [9]. In the same year, Cai Ligang et al. used improved VMD, adaptive backtracking search algorithm and least squares support vector machine to

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identify tool wear state, which solved the problems of modal aliasing and noise sensitivity [10]. In 2021, in order to better realize the monitoring of tool wear state, Cheng Xun and Yu Jianbo proposed a non-local mean denoising method based on integral image acceleration and Turky bi-weight kernel function by using the gray distribution characteristics of tool wear image, and adopted single and double threshold Otsu method and local extreme point extraction method based on morphological reconstruction method to realize image adaptive contrast enhancement and detection of wear area and boundary extraction. Compared with the current machine vision supervision method, the detection method has higher detection accuracy and efficiency [11].

Although some scholars have established the mapping relationship between signal characteristics and bit wear state through neural networks, in the signal processing link, the process of signal feature extraction will inevitably lose some time-related information [12]. In this regard, this paper proposes a drill condition monitoring and classification method based on signal imaging and deep learning. The sensor acquisition signal is imaged by the Gram angle field and classified and identified by the convolutional neural network (CNN). On the basis of retaining the original structure of the data without losing information, the recognition of the drill wear state is realized, thereby avoiding the occurrence of delamination, tearing and other defects of CFRP in the processing of parts such as non-bearing parts of automobiles, rail transit domes, wind turbine blades, pressure vessels, sporting goods and aerospace fairings and shells.

2 Correlation principle of Graham angle field

In order to retain the characteristics of the drill wear state in the original signal, this paper uses the collected one-dimensional time series signal to achieve two-dimensional imaging through the Gram angle field. Gramian Angular Field (GAF) is divided into Gramian Summation Angular Field (GASF) and Gramian Difference Angular Field (GADF). Compared with other feature processing methods, its essence is to increase the dimension of the signal to be processed, which can fully retain the feature information in the original signal [13]. The signal processing of GAF is roughly divided into three steps:

2.1 Normalization of data

First of all, it is necessary to normalize the collected signal data. The calculation formula is:

$$\tilde{A}_i(t) = \frac{(A_i(t) - A_{\max}) + (A_i(t) - A_{\min})}{A_{\max} - A_{\min}} \tag{1}$$

In the formula: $A_i(t)$ the amplitude of the normalized signal at time t, the range is [-1,1]; $A_{\max}$ and $A_{\min}$ are the maximum and minimum values in the signal sequence.

2.2 Coordinate system transformation

The signal sequence in the Cartesian coordinate system is characterized by the polar coordinate system. The calculation formula is:

$$\phi_i(t) = \arccos \tilde{A}_i(t) \tag{2}$$

$$r_i = \frac{t_i}{N} \tag{3}$$

In the formula, $\phi_i(t)$ and r_i are the angle and radius under polar coordinates; here $\phi_i(t) \in [0, \pi/2]$, $i = 1, 2, ..., N$.

2.3 Triangular transformation

After the signal is characterized by the polar coordinate system, the triangular transformation calculation formula of its amplitude is:

$$G = [\tilde{A}_i(t) \otimes \tilde{A}_j(t)]_{i,j=1}^{N} \tag{4}$$

In the formula, $\otimes$ is the inner product operation.

Based on the above formula, the Gram summation field and the difference field can be obtained by the inner product operation of the cosine function of the sum of two angles. The expression is:

$$\begin{aligned} \tilde{A}_i(t) \otimes \tilde{A}_j(t) &= \cos(\phi_i(\mathrm{t}) + \phi_j(\mathrm{t})) \\ &= \tilde{A}_i(t)\tilde{A}_j(t) - \sqrt{1 - \tilde{A}_i^2(t)}\sqrt{1 - \tilde{A}_j^2(t)} \end{aligned} \tag{5}$$

$$\begin{aligned} \tilde{A}_i(t) \otimes \tilde{A}_j(t) &= \sin(\phi_i(\mathrm{t}) - \phi_j(\mathrm{t})) \\ &= \sqrt{1 - \tilde{A}_i^2(t)} \cdot \tilde{A}_j(t) - \tilde{A}_i(t)\sqrt{1 - \tilde{A}_j^2(t)} \end{aligned} \tag{6}$$

In summary, it can be seen that both GASF and GADF are two-dimensional matrices symmetrical by the main diagonal. In matrix form can be expressed as:

$$G_{GASF}=\begin{bmatrix}\cos(\phi_1(t)+\phi_1(t)) & \cdots & \cos(\phi_1(t)+\phi_n(t))\\ \cos(\phi_2(t)+\phi_1(t)) & \cdots & \cos(\phi_2(t)+\phi_n(t))\\ \vdots & \vdots & \vdots\\ \cos(\phi_n(t)+\phi_1(t)) & \cdots & \cos(\phi_n(t)+\phi_n(t))\end{bmatrix} \tag{7}$$

$$G_{GADF}=\begin{bmatrix}\sin(\phi_1(t)-\phi_1(t)) & \cdots & \sin(\phi_1(t)-\phi_n(t))\\ \sin(\phi_2(t)-\phi_1(t)) & \cdots & \sin(\phi_2(t)-\phi_n(t))\\ \vdots & \vdots & \vdots\\ \sin(\phi_n(t)-\phi_1(t)) & \cdots & \sin(\phi_n(t)-\phi_n(t))\end{bmatrix} \tag{8}$$

Gramian matrix retains the time dependence of the signal. While converting one-dimensional time series into two-dimensional images, it not only reflects the trajectory of time series in high-dimensional space, but also reflects the degree of vector linear correlation.

3 IN-CNN state recognition model

3.1 Typical convolutional neural network structure

The convolutional neural network consists of two processing modules: feature extraction and feature mapping. The feature extraction layer is divided into convolution layer and pooling layer, which is mainly used to extract high robustness features in two-dimensional images. The feature mapping layer includes a fully connected layer and a classification layer. The main function is to classify the extracted features to achieve recognition [14].

Convolution layer: The weight sharing in the convolution layer can effectively reduce the parameters and reduce the occurrence of overfitting. From one-dimensional data, the calculation formula of convolution layer is:

$$y^{s(i,j)}=x^{s(i,j)}\times k^{s(i,j)}=\sum_{i=1}^{n}\sum_{j=1}^{n}x^{s(i,j)}\oplus k^{s(i,j)} \tag{9}$$

In the formula, $y^{s(i,j)}$ is the input of the s-th layer; $k^{s(i,j)}$ is the convolution kernel weight input at the *s*-th layer; *n* is the convolution kernel width ; $\oplus$ is convolution operation.

Activation function: In this paper, the SeLU activation function is chosen to avoid the gradient disappearance as well as the explosion problem during the calculation [15].

$$y^{S(i,j)}=\mathrm{SeLU}(y^{s(i,j)})=\lambda\begin{cases}y^{s(i,j)} & x>0\\ \alpha\cdot e^{y^{s(i,j)}}-\alpha & x\le 0\end{cases} \tag{10}$$

In the formula: $y^{s(i,j)}$ is the output after convolution operation; $y^{S(i,j)}$ is the output of the activation function.

Pooling layer: In this paper, the data space is divided into several regions by means of maximum pooling, and the maximum value in each region is selected as the output, so that the amount of calculation and the difficulty of calculation will be reduced. The maximum pooling expression is:

$$M^{s(i)}=\max\{y^{s(i,j)}: i\le i<i+n, j\le j<j+n\} \tag{11}$$

Fully connected layer: The ReLU activation function is used between the hidden layers, and the Softmax activation function is used in the output layer. The calculation formula of the fully connected layer is:

$$O_j^{s+1}=\delta(\sum_{i=1}^{n}\omega_{ij}^{s}\times\alpha^{s(i)}+b_j^{s}) \tag{12}$$

In the formula: O_j^{s+1} is the output of the j-th neuron in the *s + 1* layer; ω_{ij}^{s} is the weight between *i* neurons in the *s*-th layer and *j* neurons in the *s + 1*-th layer; b_j^s is the bias of *s* layer.

3.2 Inception-CNN neural network model

Based on the convolutional neural network established above, this paper uses the Inception module to construct the Inception-CNN model (IN-CNN) to decompose the convolution process into convolution calculation under multi-scale convolution kernels, which can effectively reduce the iteration rate. The optimized IN-CNN model framework is shown in Figure 1:

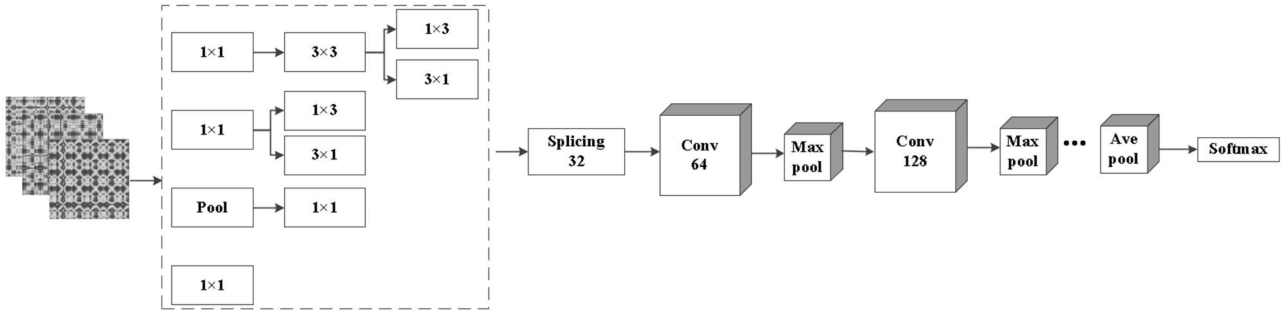


Fig. 1 *The basic process framework of IN-CNN*

The Inception module is used to change the original m × m convolution kernel into 1 × m and m × 1 convolution kernels of different scales for serial and parallel combination calculation so that there are receptive fields of different scales after convolution calculation, which improves the nonlinear feature expression ability of the model. Finally, the feature fusion of different scales is realized after splicing [16].

4 Model training and recognition process

The IN-CNN state recognition process is shown in Figure 2, including three steps: data pre-processing, training model and model identification.

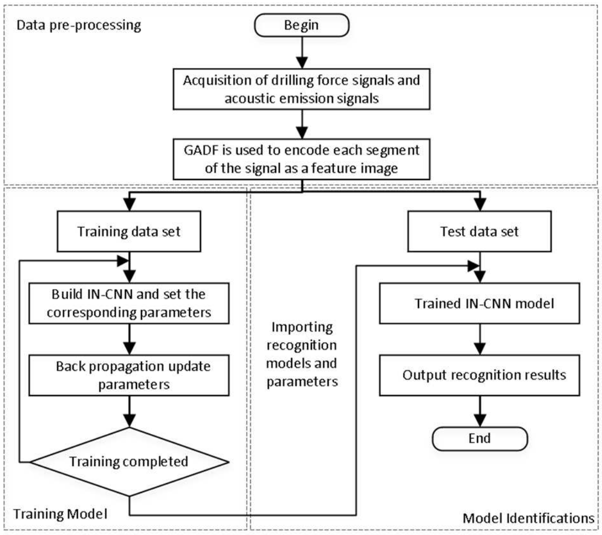


Fig. 2 *IN-CNN state recognition flow chart*

4.1 Data preprocessing

The collected drilling force signal and acoustic emission signal are processed by Gram angle field to obtain two-dimensional images of different states as input samples, and the samples are divided into multiple data sets proportionally.

4.2 Training model

The IN-CNN model is constructed and the network parameters are initialized. The pictures of the training samples are input into the IN-CNN, the network parameters of each layer are trained, and finally, the trained model is obtained.

4.3 Model identification

The test samples are input into the trained IN-CNN model to perform adaptive feature extraction and pattern recognition on the state data of the vibration drilling bit, and the recognition results are output.

5 Experimental results and analysis

5.1 Experimental data and pretreatment

In this paper, CAF is used for two-dimensional imaging of drilling force and acoustic emission signals in vibration drilling for the first time, and it is used as a monitoring signal to monitor the state of the drill bit at the same time, avoiding the limitation of using a single signal to monitor the state of the drill bit.

The schematic diagram of the axial vibration drilling device is shown in Figure 3. The components include a bench drill device, a sensor, and an axial vibration system. The main parameters of the device are set as follows: resonant frequency: 4×104Hz; amplitude: 1.3×10-2mm; spindle speed range: 3000~8000rpm; feed rate range: 1~99μm/r; axial stroke range: 0~50mm; positioning accuracy: 2μm.

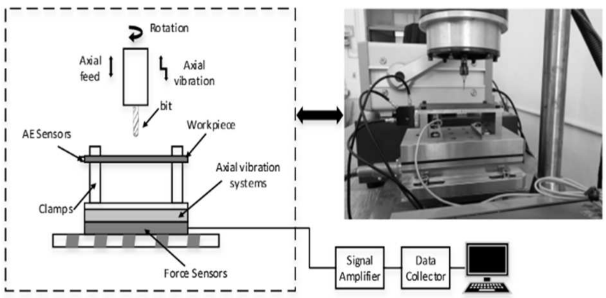
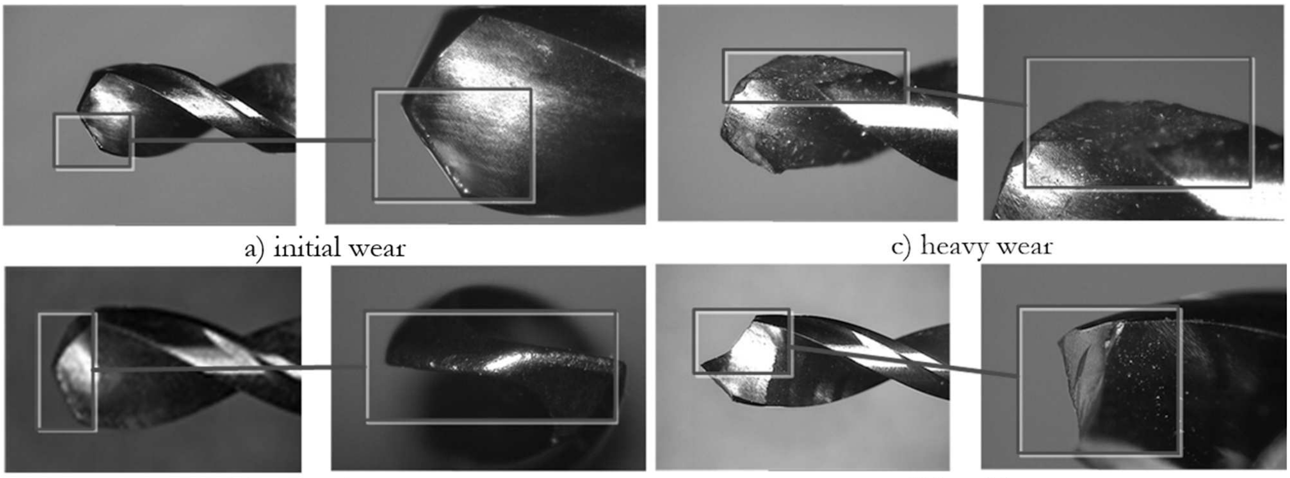


Fig. 3 *Schematic diagram of axial vibration drilling unit*

In the experiment, the drilling force signal is collected by KISTLER 9257 B piezoelectric sensor and KISTLER 5070 charge amplifier. AE signals during drilling are collected by SR150 M acoustic emission sensor. The drill bit is a 2mm twist drill, and the test workpiece is CFRP aluminum alloy material.

In the experiment, after drilling two holes, the wear state of the drill bit is measured, as shown in Figure 4.

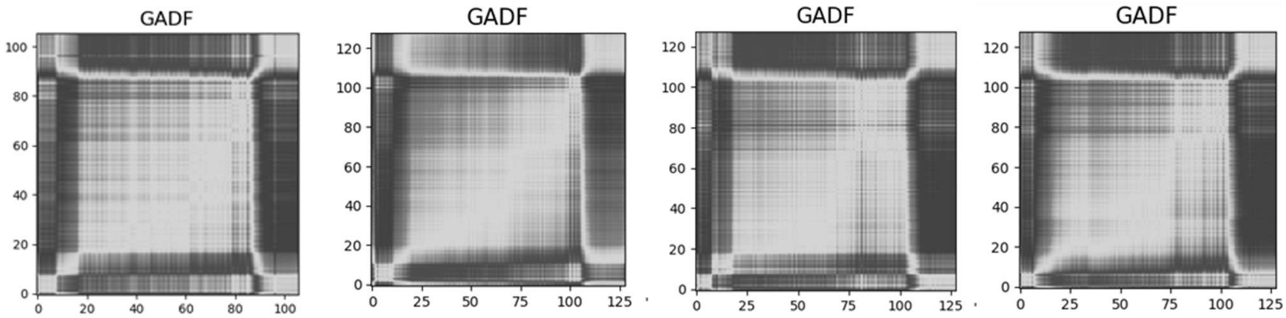


a) initial wear c) heavy wear

b) normal wear d) breaking

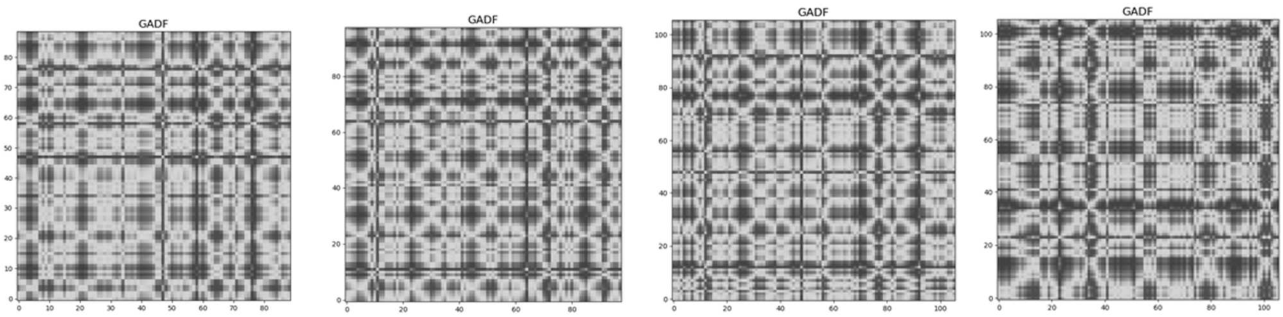
Fig. 4 *Drill different state sample diagram*

After the pre-processing stage, the drilling force signal and the acoustic emission signal during the drilling process are collected and converted into a two-dimensional image by GAF. The image resolution is 128 × 128. Figures 5 and 6 show the initial, normal, severe, and chipping states, respectively. The GADF images of the drilling force signal and the acoustic emission signal: A total of 500 3-channel images were selected, of which 60 % were used for image training and 40 % were used for testing.



a) initial stage *b) normal* *c) critical* *d) breaking*

Fig. 5 *GADF image under drilling force signal*



a) initial stage b) normal c) critical d) breaking

Fig. 6 *GADF image under acoustic emission signal*

5.2 Experimental parameters setting

In the IN-CNN network model, there are four convolutional layers with 128 convolution kernels with 1×3 and 3×1 scales; two convolutional layers with 192 convolution kernels of 1×3 and 3×1 scales; 1 convolution layer and pooling layer, including an average pooling operator with a scale of 2×2 and 64 convolution kernels with a scale of 3×3.

5.3 Experimental Process and Result Analysis

During the test, the same number of samples of drilling force signal and acoustic emission signal under the same test conditions are identified by IN-CNN neural network. The confusion matrix of its identification results is shown in Figures 7 and 8.

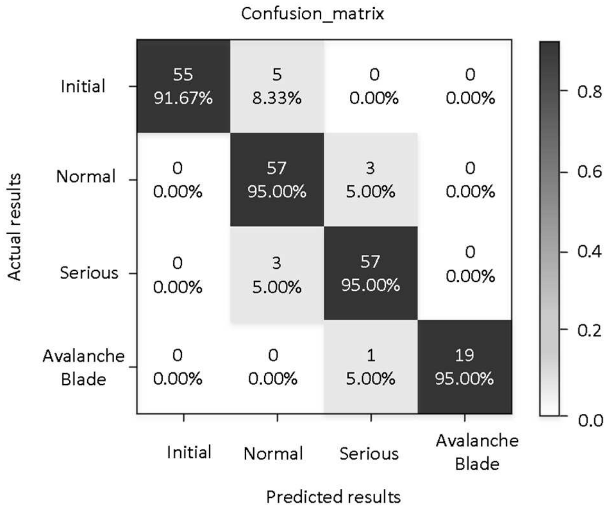


Fig. 7 *Drilling force test confusion matrix*

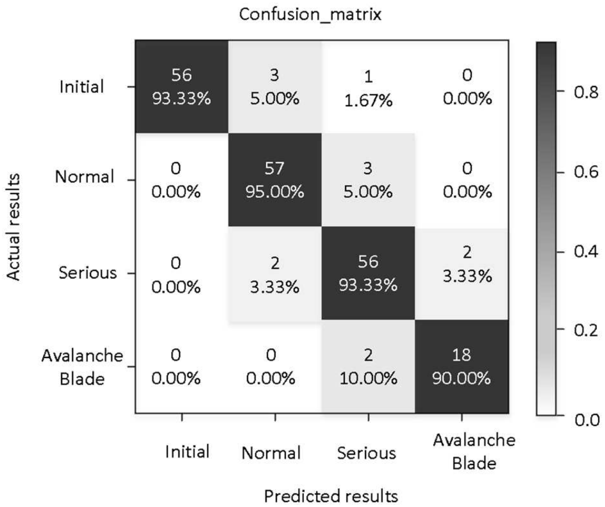


Fig. 8 *Acoustic emission test confusion matrix*

From the above recognition effect, the comprehensive recognition rate is 93.1% in the three states of drill bit wear, and the vibration signal of the chipping drill bit achieves the effect of all 20 samples. In the case of a limited number of samples, the error is less than 10%, which can meet the requirements of drill wear prediction.

5.4 Comparative analysis of different model algorithms

Under the condition that the test sample and the training sample are the same sample, the results of the traditional CNN network, BP neural network and support vector machine model for different bit wear states of vibration drilling are shown in Table 1:

Tab. 1 *Comparison of recognition results of four models*

Number	*Model*	*Training Set Accuracy*	*Accuracy of test set*
1	*BP*	*81%*	*82.5%*
2	*SVM*	*83.2%*	*85%*
3	*CNN*	*86.3%*	*90.6%*
4	*IN-CNN*	*93%*	*93.1%*

The results show that the recognition accuracy of the traditional CNN network is 90.6%, the recognition accuracy of the BP neural network is 82.5%, and the recognition accuracy of the support vector machine is 85%. IN-CNN can be well applied to the model recognition method proposed in this paper, and the comprehensive recognition rate is higher than that of a general neural network.

6 Conclusion

In this paper, according to the characteristics of force and acoustic emission signals in vibration-assisted drilling, the Gram angle field is used to convert one-dimensional time series into two-dimensional images. Based on IN-CNN, a vibration-assisted drilling bit state recognition model is established. The recognition accuracy of CNN, BP and support vector machine is compared through experiments, which has certain engineering significance for improving the machining accuracy and efficiency of composite materials and deep holes.

- 1) Aiming at the problem of ignoring the signal timing in the process of signal feature extraction and two-dimensional image, the one-dimensional time-series force and AE signal are transformed into two-dimensional image by Gram angle field, and the timing characteristics of the signal are retained.
- 2) Aiming at the problem of high misjudgment rate and poor accuracy of single signal recognition, the multi-signal deep fusion method is used to fuse the force and AE signals at one layer, and the fusion of different scale data and model generalization ability is realized.
- 3) Aiming at the multi-signal image feature fusion of vibration-assisted drilling, the Inception module is used to optimize the convolutional neural network. Through the experimental study of drill wear state, the recognition accuracy of IN-CNN method is improved by 2.5 %, 10.6 % and 8.1 % respectively compared with CNN, BP and support vector machine. The reliability of the proposed method is verified, which provides

practical significance for the efficient and high-precision machining of composite holes.

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