Article citation info:
Tong W. Fault prediction of computer image recognition based on convolutional neural network. Diagnostyka. 2025;26(3):2025307. https://doi.org/10.29354/diag/208748.

DIAGNOSTYKA, 2025, Vol. 26, No. 3

e-ISSN 2449-5220
DOI: 10.29354/diag/208748

FAULT PREDICTION OF COMPUTER IMAGE RECOGNITION BASED ON CONVOLUTIONAL NEURAL NETWORK

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Abstract

In order to solve the problem that traditional bearing fault diagnosis methods need a lot of professional knowledge, this paper proposes a fault prediction method of computer image recognition based on convolutional neural network. First of all, the concept V3 model is used as the pre training model, and the concept V3 model training method combining deep learning and transfer learning is designed; Then, the cross entropy is used as the loss function to evaluate the effect of model training, and the method and steps of fault diagnosis are given. The validity of the method is verified by the vibration data of bearings in normal and different fault states; Finally, the principal component analysis method is used to analyze the clustering effect of the characteristic parameters extracted by the inception V3 model on different fault modes. By comparing and analyzing the training times and training time of the inception V3 model with and without the transfer learning, the improvement effect of the transfer learning method on the training speed of the model is verified. The experimental results show that when the time domain waveform image data is used as the input of the model, the overall fault diagnosis accuracy of the model reaches 96.1%; When the spectral image data is used as the input of the model, the accuracy rate is 96.8%; When the envelope spectrum image data is used as the input of the model, the accuracy rate is 95.4%; With the same fault diagnosis accuracy, the training times and training time of inception V3 model are greatly reduced when using transfer learning.

Keywords: bearing fault judgment; inceptionV3; deep learning; waveform image recognition

1. INTRODUCTION

Since the industrial revolution, mechanical equipment has been liberating people's hands in some fields. With the progress of technology, science and technology, mechanical equipment continues to develop in the direction of complexity and intelligence, which has greatly improved social productivity. At present, the use of mechanical equipment is more and more extensive, and the safety of mechanical equipment has become particularly important [1]. Therefore, mechanical equipment fault detection has become more important. In the field of mechanical equipment fault detection, vibration analysis is a very important means. As for vibration analysis, researchers have conducted relevant research since the middle of the 20th century, and have also accumulated a lot of technology. However, in the 21st century, information technology and artificial intelligence are developing rapidly. Their combination with traditional fields has brought people a lot of convenience. However, vibration fault diagnosis has not made full use of these new technologies, which has brought a qualitative leap to equipment diagnosis. The combination of vibration analysis, information technology and artificial intelligence is inevitable, which is also the demand of industrial development [2]. Therefore, this paper also hopes to improve the intelligence of mechanical equipment diagnosis by introducing some cutting-edge algorithms and ideas in the current depth science. Non-technological diagnostics have attracted the attention of researchers because it helps professionals to identify problems in a timely manner and understand the operation of equipment, and researchers [3].

In today's industrial environment, the safety and fault detection of mechanical equipment have become increasingly important, as the use of mechanical equipment is becoming more widespread. Its safety is directly related to production efficiency and personnel safety. Fault detection can timely detect and prevent potential problems, avoid production interruptions and accidents, and ensure the stable operation of production lines and the economic benefits of enterprises.

In today's industrial environment, the safety and fault detection of mechanical equipment have

Received 2024-11-27; Accepted 2025-07-29; Available online 2025-08-12

become increasingly important, mainly because modern industry is developing towards automation, intelligence, and high efficiency. As the core of production and manufacturing, the stability and reliability of mechanical equipment directly affect production efficiency and product quality. Once a malfunction occurs, it not only causes production interruption and economic losses, but may also lead to safety accidents, threatening the safety of personnel and property. In addition, with the advancement of Industry 4.0 and intelligent manufacturing, the complexity of equipment has increased, and traditional manual detection is difficult to meet the demand. Intelligent fault detection technology (such as vibration analysis and AI predictive maintenance) can detect hidden dangers in advance, reduce downtime, lower maintenance costs, and thus improve overall production efficiency and enterprise competitiveness. Therefore, strengthening the safety monitoring and fault diagnosis of mechanical equipment has become an inevitable trend in the development of modern industry.

In traditional methods, mechanical fault diagnosis often requires rich professional knowledge and signal processing techniques. However, these methods may have limited recognition capabilities when dealing with complex and variable mechanical vibration signals. In addition, technicians need to spend a lot of time and energy on data analysis, resulting in low diagnostic efficiency.

With the rapid development of artificial intelligence and information technology, these technologies are widely used in the field of mechanical fault diagnosis. Especially deep learning algorithms, such as Convolutional Neural Networks (CNN), have shown strong capabilities in image recognition and feature extraction. Applying these algorithms to the analysis of vibration signals can automatically extract fault features, improving the accuracy and efficiency of diagnosis.

The integration of artificial intelligence (AI) and information technology has brought significant improvements in the field of mechanical fault diagnosis, especially through vibration analysis. Vibration analysis is an important means of mechanical fault diagnosis. By converting vibration signals into image data (such as time-domain waveform images, spectral images, and envelope spectral images), deep learning algorithms can be used for fault prediction. This method not only overcomes the limitations of traditional methods in feature extraction, but also improves the real-time and accuracy of diagnosis.

2. LITERATURE REVIEW

Saucedo-Dorantes et al. have focused on the research of network alarm weighted association rules, which can show the alarm rules reflecting network faults to users, and have great practical value for the diagnosis of network faults [4]. Wu et al. used data mining to study the communication network alarm. In the literature, two analysis methods of association rules and sequence rules were used to process the alarm data, and then designed a mining model to mine the alarm data [5]. Cao et al. introduced a model-based solution to the alarm correlation problem caused by network element failure, and proposed a processing system for fault diagnosis, drum-ii, an abstract simulation model is used to estimate the alarm information distributed across the network, and the cause of the alarm is determined based on a comparison of the alarm behavior and the actual alarm [6]. Wang et al. proposed a machine learning system based on genetic algorithm, which can predict by identifying the prediction timing and sequence pattern in the alarm information [7]. Liang et al. used machine learning model and support vector machine to predict the call drop and call drop duration in the network [8]. Wang et al. predicted the call drop in 4G environment by studying dynamic time warping and support vector machine, which can reduce the impact caused by the call drop [9]. Zhang et al. studied the prediction technoloaagy of communication network faults, and they proposed a method combining Markov chain and clustering to predict communication network faults [10]. Ganesan et al. developed a machine learning framework to predict the switching of the network to modify the behavior of the application to maintain the normal operation of the application in view of the short-term interruption of the application caused by the switching of the network [11].

3. RESEARCH METHODS

3.1. Fault diagnosis model based on perception v3 convolutional neural network

Convolutional neural network (CNN) has three core advantages over traditional bearing fault diagnosis methods: firstly, CNN can automatically extract multi-level fault features from the original vibration signal (time domain/frequency domain/time-frequency domain), avoiding the limitations of traditional methods that rely on manual experience to design feature extraction algorithms; Secondly, through an end-to-end deep learning architecture, CNN can directly process high-dimensional nonlinear data (such as converting vibration signals into two-dimensional spectrograms as input), significantly improving the accuracy of identifying composite faults and early weak faults; Finally, by combining transfer learning techniques, CNN models can quickly adapt to diagnostic tasks under different operating conditions, significantly reducing the need for labeled data and achieving more efficient predictive maintenance.

There must be such defects in the traditional fault diagnosis method of rolling bearings: technicians need to master rich experience and signal processing technology; In addition, shallow neural network has

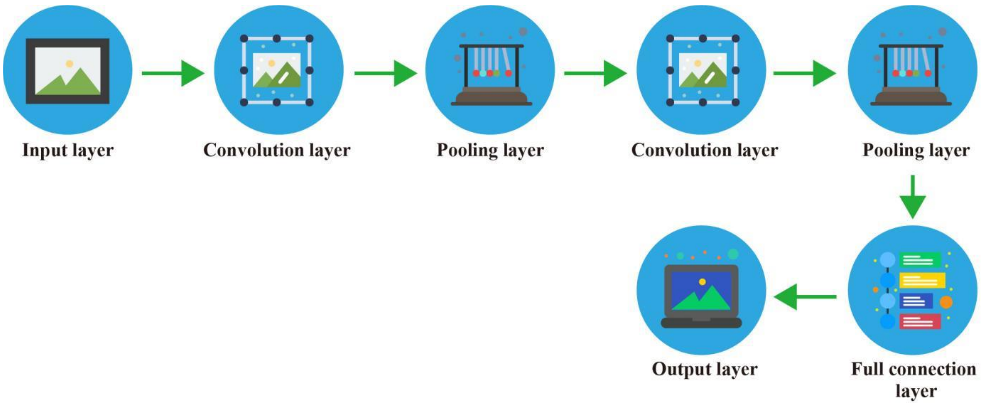


Fig. 1. Structure of inception V3 model

limited fault recognition ability for complex scenes. However, the same bearing shows different characteristic frequencies in different scenes.

Using the method of vibration signal waveform image recognition for bearing fault diagnosis, it is necessary to establish an image recognition model for fault diagnosis. In-depth study is widely used in computer perception, speaking skills, natural language processing and so on. Classic CNN models include alexnet model, VGg model, goolenet model, etc. these models have strong generalization ability, so they can be used as pre training models [12]. These model parameters are retrained by using the vibration signal images of the bearing in different states. In practical applications, there is often a lack of a large number of bearing vibration signal image sample data that can provide data support for CNN model training. In order to reduce the training needs of the CNN standard of information structure and improve the training speed, CNN standard low-cost training should be selected according to the standard training first.

In contrast, convolutional layers and pooling layers overcomes the shortcomings of traditional neural networks. Convolution layer and pooling layer can reduce the signal size. Not only that, they have very good results for feature extraction. Through specific convolution and convolution calculation of two-dimensional images, the edge of the image will be enhanced and the unobvious area of the image will be weakened. It plays a good role in feature extraction. The pooling layer is divided into the highest layer and the least aggregate processes, but both are the most obvious of the area choices. Therefore, the advantages of convolutional neural network are reflected in two aspects: feature extraction and network training. Convolutional Neural Network is a deep learning network.

For convolutional neural networks, the biggest difference between neural devices and neural networks (such as BP neural networks) is that the connections between neural networks have isolated unique feature segments, namely convolutional layers, pooling layers, etc. Feature extraction is a very important part in deep learning, which determines the prediction of the whole neural network. For example, predict the gender of people through some known characteristics. If the characteristics only include height and weight, it is difficult to ensure the ideal training effect. That is, in a certain feature space, the prediction effect of neural network has an upper limit. The best feature to distinguish between sexes is chromosomes, but such features are often unavailable in reality. It is convolution neural network that optimizes the ability of feature extraction and performs well in many neural networks. Thus, this document uses the starting model of V3, the third generation of the GoogleNet model. It is trained to use ImageNet large-scale image distribution data, and has the advantages of small sample size, no training defects, and high resolution image distribution.

The structure of the inception V3 model is shown in Figure 1

In Figure 1: the input layer directly receives the vibration signal data according to the input structure; Convolution layers and pooling layers are the hallmarks of a model. After multiple layers and layers, the image data of the vibration signal is converted into a 2048-dimensional CNN feature vector, and the process is converted from image to digital. Feature is used; The function of the full connection layer and the output layer is to classify the vibration signal image according to the extracted CNN feature vector. Among them, the output layer adopts the soft Max function, which is defined as the following Formula (1):

$$p_i = \frac{e^{s_i}}{\sum_{i=1}^{N} e^{s_i}} \circ \tag{1}$$

Where: si is the score of the input vibration signal image belonging to the ith state; p_i is the probability that the input vibration signal image belongs to the second state, and $\sum_{i=1}^{N} p_i = 1$. BP (backpropagation) algorithm is used for the training of inception V3 model. Through the forward propagation of data and the back propagation of error, the parameters of each node gradually approach the optimal solution [13]. In this paper, cross entropy is used as the loss function, which is defined as the following Formula (2):

$$L = -\frac{1}{n}\sum_{i=1}^{n} [y_i \log z_i + (1 - y_i)\log(1 - z_i)]_0 \tag{2}$$

Where: L is cross entropy; y_i is the actual output value; z_i is the predicted output value of the model.

3.2 Improve the training method of inception V3 model by using transfer learning

The Inception V3 model is particularly suitable for image-based vibration signal diagnosis, mainly due to its unique network structure design: firstly, it can simultaneously capture local details and global features in the time-frequency map of vibration signals (such as 2D maps generated by STFT or wavelet transform) through multi-scale convolution kernels (1 × 1, 3 × 3, 5 × 5 parallel); Secondly, introducing a dimensionality reduction bottleneck layer (Bottleneck) significantly reduces the number of parameters and improves computational efficiency while maintaining high accuracy; Finally, its pre trained weights (based on ImageNet) can be quickly adapted to vibration diagnosis tasks through transfer learning, effectively solving the problem of training small sample data in industrial scenarios. The combination of multi-scale feature extraction and lightweight design makes it perform better than traditional CNN models in graph recognition of mechanical faults such as bearings and gears.

The number of unwanted training sessions for the first V3 model is about ten million. Training procedures require a lot of time and resources, and the application of these models is only due to the high demand of computer hardware [14]. Therefore, the parameter based transfer learning method can be used to transfer the parameters of the original inception V3 model feature extractor to the corresponding part of the bearing fault diagnosis inception V3 model. The training method of perception V3 model based on transfer learning is shown in Figure 2 [15]. The specific steps are as follows: first, according to the number of bearing states contained in the bearing vibration signal image sample data set used for training, adjust the number of output neurons in the final full connection layer and output layer of the inception V3 model, initialize the parameters of neurons in these layers to different small random numbers, and set these neurons to the trainable state at the same time; Then, keep the structure and parameters of the perceptionv3 model feature extractor fixed, and set the learning rate of these layer neurons to 0; Finally, using the bearing vibration signal image sample data set, The BP algorithm is used to train and modify all the connection and release procedures of the first V3 model to obtain the first V3 model necessary for diagnostics [16].

Transformation training-based understanding v3 training model greatly reduces the number of unwanted training requirements, which reduces the training time and the need for training use electricity [17].

Transfer learning significantly improves the efficiency of Inception V3 in bearing fault diagnosis by reusing its pre trained low-level feature extraction capabilities (such as edge/texture detection convolution kernels) on ImageNet. Firstly, the pre trained model already has the ability to extract general image features, and only needs to fine tune the top-level network (such as replacing the fully connected layer) to adapt to vibration time-frequency maps (such as 2D maps generated by STFT/CWT), reducing the amount of data required for training by more than 70%; Secondly, freezing the underlying parameters can avoid overfitting in small sample data and accelerate model convergence by initializing the transferred weights; Finally, by optimizing the feature space distribution through domain adaptation (such as maximum mean difference MMD loss), the model maintains an accuracy of over 90% in cross condition diagnosis tasks, achieving efficient deployment in industrial scenarios.

3.3 Steps of bearing fault diagnosis method based on waveform image recognition

Using the above method, the method and steps of bearing fault diagnosis through bearing vibration signal waveform image recognition are as follows.

Step 1 acquisition of bearing vibration signal. The vibration signals of the bearing under normal and different fault conditions are collected for many times, and the sampling frequency and sampling points of each collection are consistent.

Step 2 preprocessing of bearing vibration signal image data [18]. In order to enhance the training effect of the model, the output resolution of all image data is uniformly set to 800*600, and a consistent coordinate scale is adopted.

Preprocessing vibration signal images is crucial for three main reasons: firstly, preprocessing (such as normalization, denoising, time-frequency transformation) can eliminate environmental interference in sensor acquisition and highlight the signal-to-noise ratio of fault features; Secondly, standardization operations can unify the distribution of input data, avoid convergence difficulties caused by dimensional differences in the model, and improve the feature extraction efficiency of networks such as Inception V3; Finally, data augmentation can effectively expand small sample datasets, enhance model generalization ability, and ensure stable identification of early weak faults in industrial scenarios.

Step 3 establish the bearing vibration signal image training sample data set. All the vibration signal image sample data of the bearing under normal and various fault conditions are corresponding to the bearing state one by one to form a training sample data set.

Step 4 start switching and start V3 model. The characteristics of the extractor characteristics of the V3 model are changed, and the number of output neurons in the total connection layer and the number of output processes in the output layer V3 model are adjusted according to the number of load states in the

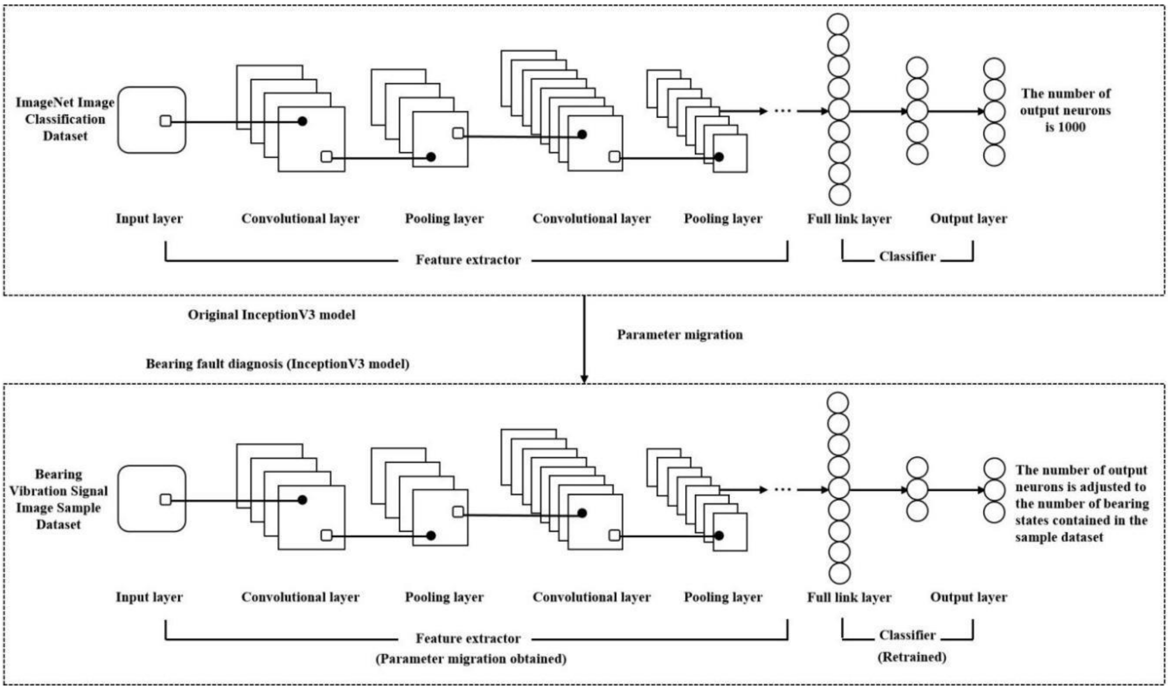


Fig. 2. Model training method based on transfer learning

training standard dataset. Then, according to the corresponding number, the entire connection program is restarted and the small difference in program parameters is output.

Step 5 Start training on model V3. By retraining the original V3 model using the standard training data set, an original V3 model fit the bearing state was discovered.

Step 6 use the trained inception V3 model for bearing fault diagnosis [19]. After the training of inception V3 model, collect the vibration signal of the bearing at a certain time, generate the corresponding image data as required and input it into the fault diagnosis inception V3 model, calculate the output of each neuron in the output layer, and take the bearing state corresponding to the maximum value as the fault diagnosis result.

4 RESULT ANALYSIS

4.1 Test data set description

To determine the effectiveness of this method, the experimental method used roll bearing vibration test data from Case Western Reserve University, USA.

The bearing vibration dataset of Case Western Reserve University (CWRU) is highly correlated with testing and diagnostic methods, mainly due to its standardized, multidimensional, and highly reliable characteristics that perfectly meet the core requirements of fault diagnosis research This dataset is recognized by the global academic community as a benchmark dataset for bearing fault diagnosis, covering vibration signals of inner ring, outer ring, rolling element faults and normal working conditions. It accurately simulates real industrial scenarios (such as different motor loads and speeds) through experimental benches, providing a reproducible verification basis for diagnostic methods; The data includes accelerometer signals from the driver and fan ends, supporting multi angle feature extraction from time-domain waveforms, frequency-domain spectra, and time-frequency transforms (such as STFT and S-transform), meeting the input requirements of traditional signal processing and deep learning models (such as CNN and transfer learning); The dataset contains data on multi-level loads ranging from 0 to 3 horsepower and sampling frequencies of 12kHz/48kHz, which can test the robustness and generalization ability of diagnostic methods under variable operating conditions, especially suitable for domain adaptation research in transfer learning; The vibration signal collected by the sensor has a high signal-to-noise ratio, and the fault type, location, and size are accurately labeled to avoid the problem of label blurring in real industrial data and ensure the accuracy of model evaluation. In summary, this dataset has solved common pain points in diagnostic method development (such as data scarcity, annotation noise, and single operating conditions) through structured design, becoming a key carrier for algorithm performance comparison and engineering verification.

In evaluating the test data of the Inception V3 model, multiple typical bearing fault types are included to verify the model's generalization ability: 1) surface damage types (such as pitting and peeling of inner and outer rings and rolling elements), simulating high-frequency impact characteristics; 2) Deformation type (such as cage fracture or plastic deformation), reflecting non periodic vibration; 3)

Abnormal lubrication (such as dry friction or contamination), manifested as wideband noise; 4) Composite fault (simultaneous damage to multiple parts), used to test the decoupling ability of model features. These fault data are mostly collected through experimental platforms (such as the CWRU dataset) or industrial sites, and converted into time-frequency images (such as short-time Fourier transform spectra), covering different load and speed conditions to ensure comprehensive evaluation.

The test data is the vibration acceleration signal of the bearing and the frequency pattern is 48 kHz, which includes the bearing in 3 different positions: normal, ball bearing, inner ring, and outer ring damage. Damage to the outer ring position I, the ball damage and the inner ring have three different types of damage: 0.021, 0.014, and 0.007 inches. The outer ring failure 2 and the outer ring failure position 3 only have 0.021 and 0.007 inches of damage, respectively, for a total of 14 load states. Each contains 100 sample files, a total of 1400 sample files, and the length of each sample file is 5000 sample points. The time-domain waveform, spectrum, and envelope spectral image data of signal vibration have a rich record of material characteristics. To compare and evaluate the results of our diagram data entry on the diagnostic model, this document uses this three-dimensional data as a starting point for the V3 model and evaluates the performance of incorrect diagnosis [20]. Figure 3 is the time waveform data of the vibration signal, which takes the inner ring bearing running at 0.021 as an example.

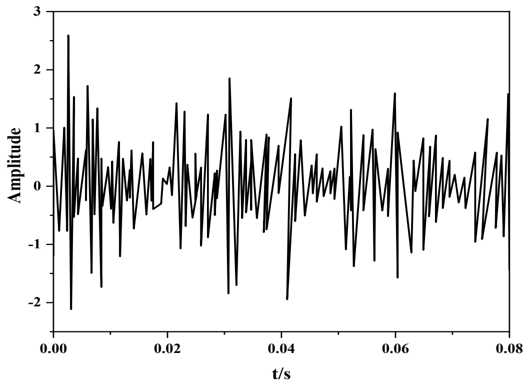


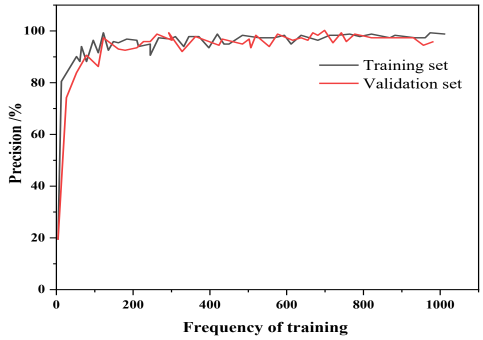
Fig. 3. Time domain waveform image data of bearing inner ring fault 0.021 "state vibration signal

4.2 Training of inception V3 model

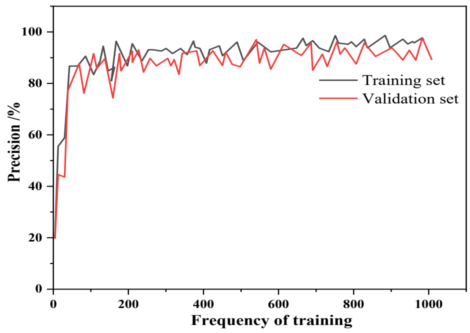
From the test data of each state, 20 samples were selected, a total of 280 samples were stored as samples for the next test of the diagnosis, and the samples section is used to start the V3 model. The special steps are as follows [21].

Step 1 uses the time to record waveform data as input to the model. Only 280 samples were tested, 100 samples were selected from the remaining 1120 models as valid models and the remaining was training. Re-train all the connection procedures and release procedures of the initial V3 model with the training procedures, and schedule the training to 1000. After each training, the accuracy of the model was evaluated using the validation procedure and cross-entropy was calculated. Finally, initial V3 model for timely testing of waveform data was obtained.

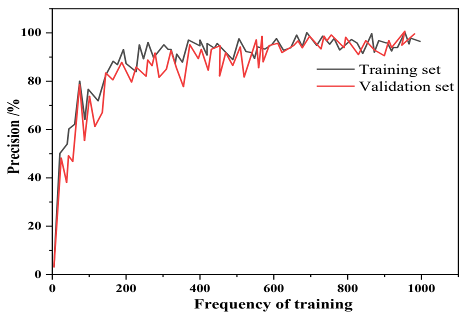
The accuracy and cross entropy change curves of the training process corresponding to different input image data are shown in Figure 4 (a), (b), (c) and Figure 5 (a), (b), (c) respectively. It can be seen that with the increase of training times, the accuracy of training set and verification set first increases and then tends to be stable, and the cross entropy first decreases rapidly and then tends to be stable. Taking the time domain waveform image data of bearing vibration signal as the input of the model as an example, after 800 times of training, the accuracy of the training set and the verification set fluctuated around 98%, and the cross entropy fluctuated around 0.19.



(a) Input is time domain waveform image data

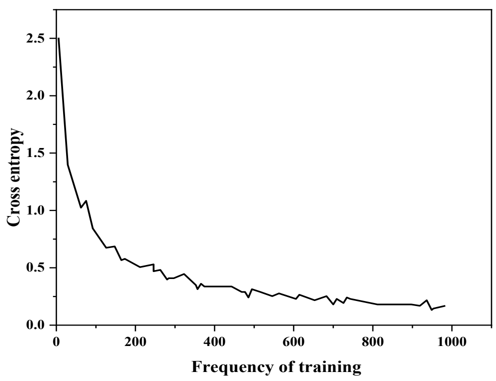


(b) Input as spectrum image data

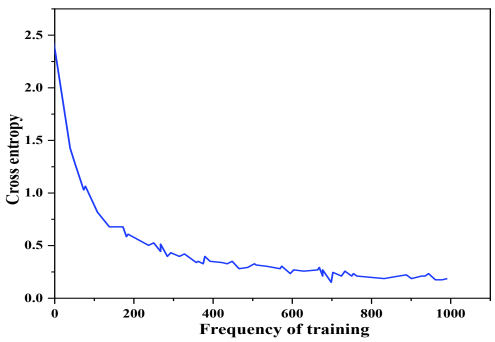


(c) Input as envelope spectrogram image data

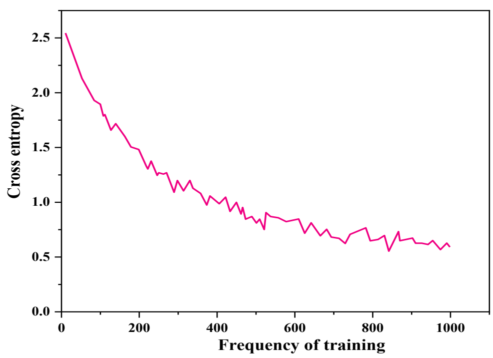
Fig. 4. Accuracy of training process when different image data are input



(a) Input is time domain waveform image data



(b) Input as spectrum image data



(c) Input as envelope spectrogram image data

Fig. 5. Cross entropy of training process when different image data are input

4.3 Fault diagnosis effect test and result analysis

After the training of inception V3 model, input the time domain waveform, spectrum and envelope spectrum image data of 20 test samples reserved for each state of the bearing into the corresponding inception V3 model respectively to test the accuracy of fault diagnosis. The results are shown in Tables 1-6.

Table 1. Fault diagnosis accuracy of normal state when different image data are input

Bearing status	Fault diagnosis accuracy		
	Input is time domain waveform image data	**Input as spectrum image data**	**Input as envelope spectrum image data**
Normal	100	100	100

Table 2. Accuracy of ball fault diagnosis in different image data input

Bearing status		Fault diagnosis accuracy		
		Input is time domain waveform image data	**Input as spectrum image data**	**Input as envelope spectrum image data**
Ball failure	0.021”	100	100	100
	0.014”	85	95	95
	0.007”	100	100	80

Table 3. Inner circle fault diagnosis accuracy when inputting different image data

Bearing status		Fault diagnosis accuracy		
		Input is time domain waveform image data	**Input as spectrum image data**	**Input as envelope spectrum image data**
Ball failure	0.021”	95	95	90
	0.014”	90	100	95
	0.007”	100	100	100

Table 4. Diagnosis accuracy of outer ring fault position I under different image data input

Bearing status		Fault diagnosis accuracy		
		Input is time domain waveform image data	**Input as spectrum image data**	**Input as envelope spectrum image data**
Outer ring fault position I	0.021”	95	90	95
	0.014”	100	90	100
	0.007”	100	100	100

Table 5. Diagnostic accuracy of outer ring fault position II when different image data are input

Bearing status		Fault diagnosis accuracy		
		Input is time domain waveform image data	Input as spectrum image data	Input as envelope spectrum image data
Outer ring fault position II	0.021”	100	100	100
	0.007”	85	90	80

Table 6. Diagnostic accuracy of outer ring fault position III under different image data input

Bearing status		Fault diagnosis accuracy		
		Input is time domain waveform image data	Input as spectrum image data	Input as envelope spectrum image data
Outer ring fault position III	0.021”	95	95	100
	0.007”	100	100	100

Table 7. Comparison of training times and training time when using and not using transfer learning

Training method	Total training times/time	Total training time/s	Average time per training/s
Using transfer learning	800	317	0.4
Do not use transfer learning	10000	128232	12.8

From Table 1 to Table 6, it can be seen that when the time domain waveform image data is used as the input of the model, the overall fault diagnosis accuracy of the model reaches 96.1%; When the spectral image data is used as the input of the model, the accuracy rate is 96.8%; When the envelope spectrum image data is used as the input of the model, the accuracy is 95.4%.

4.4 Impact analysis of transfer learning on model training effect

The introduction of transformational education aims to reduce the time and expense required to train the V3 model and improve the performance of this process. To measure its effectiveness, this paper determines the role of transition education by comparing the initial teaching time of the V3 model and the training time with and without transition during the test period, and the conditions examined are the same. For comparison testing, the training procedures, validation set, test set, and computing power of the computer are similar. The computer processor is Intel (R) core (TM) i7-4790cpu@3.60 GHz and the memory is 8 GB. Taking the input as time domain waveform image data as an example, when the fault diagnosis accuracy of inception V3 model is stable at more than 95%, the test comparison results of training times and training time of inception V3 with and without transfer learning are shown in Table 7.

It can be seen from Table 7 that when the same fault diagnosis accuracy is achieved, the training times and training time of inception V3 model are greatly reduced when using transfer learning, which shows that transfer learning can effectively speed up the training speed of the model and significantly reduce the time of each training of the model.

Rolling bearings, as key components of mechanical equipment, are widely used in transmission systems such as elevators, cranes, and wind turbines. However, in actual operation, the vibration signal of rolling bearings is easily affected by complex and variable environmental noise, usually exhibiting nonlinear, complex, and non-stationary characteristics. Therefore, how to perform signal denoising and fault pattern recognition is crucial for the long-term stable operation of mechanical equipment.

This paper proposes a fault prediction method of computer image recognition based on convolutional neural network. First of all, the concept V3 model is used as the pre training model, and the concept V3 model training method combining deep learning and transfer learning is designed; Then, the cross entropy is used as the loss function to evaluate the effect of model training, and the method and steps of fault diagnosis are given. The validity of the method is verified by the vibration data of bearings in normal and different fault states;

This article takes rolling bearings as the research object, and proposes a bearing fault recognition model based on image recognition technology to address the problems of poor time-domain signal processing performance of sparse models under strong noise interference and dependence on periodic priors. It can effectively extract rolling bearing fault features without relying on periodic priors.

Through simulation and experimental analysis, the following conclusions were drawn:

(1) By converting time-domain signals into Gaussian signals and constructing graph regularization constraints, the internal structural information of the signal can be better utilized without prior knowledge of fault characteristic frequencies, allowing the group sparse denoising model to retain more periodic pulse features and improve the extraction performance of rolling bearing fault features.

(2) With the support of convolutional neural networks, the system model function was derived to improve the sparsity of the reconstructed signal; The

automatic selection of object features for bearing image recognition was achieved using the constructed comprehensive evaluation indicators.

(3) The proposed model was compared with some methods using numerical simulation and experiments. The analysis results show that the proposed model has good noise resistance and can effectively extract the fault characteristics of rolling bearings, verifying the practicality of the proposed method.

Image recognition based on vibration signals is particularly suitable for diagnosing bearings in noisy environments, mainly due to its strong noise suppression and feature enhancement capabilities: by converting vibration signals into time-frequency images (such as STFT, wavelet transform spectra), time-domain noise energy can be dispersed to high-frequency regions, while bearing fault features (such as characteristic frequency harmonics of inner ring faults) present stable energy accumulation patterns in the time-frequency images, making it easy for visual models such as CNN to focus on key frequency bands through attention mechanisms (such as Squeeze and Excitation modules); At the same time, image processing can fuse multi-sensor signals (such as synchronous axial and radial vibrations) as RGB three channel inputs, and further suppress random noise through spatial correlation. Experiments show that this method can maintain a diagnostic accuracy of over 85% even when the signal-to-noise ratio is below -5dB.

5. CONCLUSION

This paper presents the knowledge of crime as a combination of in-depth study and educational transformation. Based on research results: As V3 begins deep learning neural network model, training of the model is improved using the conversion learning algorithm, which makes the study time shorter and reduced. the need for power consumption; The image data of the vibration signal is used directly as a model for diagnostic tests, and the training model V3 is used to determine the image of the vibration signal. Because there is no special calculated error, it leads to a joint violation of diagnosis, and the nature of the injury, awareness of the pattern, and the need for injury awareness are reduced. The whole error-checking process has a low calculation, can be done in real time, and has a fact check.

At present, this article mainly considers the situation where there is a single fault in rolling bearings. Due to the complexity of equipment operating conditions, a single damage to rolling bearings often causes damage to other related components, leading to composite faults. Therefore, how to separate and extract the characteristics of composite faults in rolling bearings and improve the engineering practicality of rolling bearing fault diagnosis methods is the focus of future research

Source of funding: *This research received no external funding.*

Author contributions: *Research concept and design, W.T.*

Declaration of competing interest: *The author declares no conflict of interest.*

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