Fault Diagnosis of High-Speed Railway Track Grinding Motor Using Convolutional Neural Network

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***Abstract*—Electric motors are common devices widely used in the industrial sector, making the study of motor fault diagnosis highly representative. In particular, for rail grinding vehicles, which play a significant role in the preventive maintenance and periodic upkeep of railway tracks, ensuring optimal train operation is of paramount importance. However, due to harsh operating conditions, the grinding motors on rail grinding vehicles frequently experience failures. Typically, these motors are periodically inspected and repaired by railway workers, which often leads to delayed handling of faulty motors, thereby compromising the efficiency of rail grinding operations and increasing the maintenance costs associated with motor repairs. Consequently, there is a need to investigate a fault diagnosis model for grinding motors and establish a system for remote fault diagnosis of these motors. To address this issue, the first step involves analyzing the maintenance records of grinding motors to identify common failure locations and types, and subsequently collecting corresponding vibration data. Next, a fault diagnosis model is developed based on the specific failure characteristics of grinding motors. This model is trained and optimized using a data set of vibration data from grinding motors to determine a suitable fault diagnosis model for this specific application. Finally, the developed fault diagnosis model for grinding motors is applied to diagnose faults in these motors, thereby validating the practical effectiveness of the model. By conducting this research, it is anticipated that a comprehensive understanding of the fault diagnosis process for grinding motors can be achieved, leading to the implementation of a remote fault diagnosis system for these motors. Ultimately, this will contribute to improved operational efficiency and reduced maintenance costs in rail grinding operations.**

Keywords—fault diagnosis, auto-encoder, convolutional neural network, motor, vibration signal

I. Introduction

In recent years, the high-speed rail network in China has experienced rapid growth, reaching a total length of 42,000 kilometers by 2022. Consequently, various issues such as rail edge wear, uneven profile grinding, contact damage, poor joint and weld flatness, and lateral grinding have become more prevalent, significantly impacting the safety and stability of railway operations. To address these challenges, rail grinding vehicles are frequently employed for maintenance and upkeep of the railway tracks. Among the crucial components of these vehicles, grinding motors play a pivotal role. These motors drive the rotation of the grinding wheel, which corrects irregular wear patterns, wheel-rail contact damage, rectifies yaw deviations, and eliminates defects on the contact surface between the wheel and rail, as shown in Figure 1 and Figure 2.

Fig. 1. rail grinding vehicle

Fig. 2. Rail grinding motor

However, the environment in which rail grinding takes place is often harsh, susceptible to factors such as windblown debris, rain, snow, extreme heat, and severe cold. Furthermore, the grinding process generates a substantial amount of iron filings that can enter the motor and cause malfunctions. Additionally, the high power, temperature, speed, and heavy load characteristics of the grinding motors make them prone to failures. These factors collectively contribute to a high failure rate of grinding motors, significantly impacting the quality and efficiency of the rail grinding process.

The faults of grinding motors can be categorized into mechanical faults and electrical faults, commonly including short circuits, abnormal grounding, bearing damage, and unbalanced shaft systems. In the event of a grinding motor failure during grinding operations, the maintenance of the track cannot continue, often requiring disassembly and returning to the factory for repairs. This poses challenges such as the inconvenience of disassembly and installation, high repair costs, and long repair cycles. Therefore, there is an urgent need for an online fault diagnosis method and system for grinding motor faults diagnosis.

Intelligent fault diagnosis of grinding motors [1][2] is an important means of motor fault diagnosis to improve motor reliability and reduce maintenance costs, and is being valued by more and more scholars. Therefore, this article conducts efficient, accurate, and intelligent fault diagnosis of the grinding motor to effectively reduce the maintenance cost of the grinding motor and improve the grinding quality and efficiency of the track.

II. Related works

In recent years, there has been rapid development in the field of artificial intelligence (AI) technology. Algorithms such as encoder-decoder, transformer, and GPT have gradually improved and been applied, bringing new advancements to fault diagnosis techniques. Various deep learning models[3][4], including convolutional neural networks[5], stacked autoencoder[6], and deep belief networks[7], have already been employed in mechanical fault diagnosis [8].

Saidi et al. [9] proposed a vibration-based fault diagnosis and prediction method for high-speed shaft bearings (HSSB) in wind turbines, utilizing a data-driven approach based on spectral kurtosis (SK). The superiority of degradation evaluation indicators derived from SK was demonstrated through the training and testing of a support vector regression (SVR) model for predicting the lifespan of HSS.

Saravanan et al. [10] employed discrete wavelet transform for feature extraction to represent all possible transient types occurring in the vibration signals generated by gearboxes. The features extracted through wavelet transform were then fed into a neural network to handle the vibration signals of gearboxes under different conditions, achieving fault classification for the gearboxes.

Gang et al. [11] proposed a novel method for gear fault recognition based on the Hilbert-Huang Transform (HHT) and Self-Organizing Map (SOM) neural network. Firstly, the frequency series of gear vibration signals were effectively separated using Empirical Mode Decomposition (EMD). Then, the Hilbert spectrum and Hilbert marginal spectrum were obtained by performing Hilbert transform on the Intrinsic Mode Functions (IMFs). These spectra displayed the amplitude variations of the gear vibration signals with respect to time and frequency. After HHT, the energy percentage of the first six IMFs was selected as the input vector for the SOM neural network, enabling the classification of gearbox faults.

From these studies, it is evident that the application of AI in fault diagnosis has become a research hotspot and an important direction for the advancement of fault diagnosis techniques. The integration of intelligent diagnostic methods, remote fault diagnosis technologies, intelligent sensor networks, and intelligent warning decision-making systems will be the future trend in the development of mechanical fault diagnosis techniques [12][13].

III. Proposed method

Common types of faults in grinding motors include electrical faults such as rotor winding faults, stator winding faults, and air gap eccentricity faults, as well as mechanical faults such as rolling bearing faults, rotor unbalance faults, and faults caused by poor installation and commissioning. To identify these faults through algorithm models, data collection of the grinding motor is necessary. The commonly used data types include vibration signals, temperature signals, and electrical signals.

Among them, vibration signal is the most commonly used fault signal. Before the motor completely fails, whether it is a mechanical fault or an electrical fault, the vibration signal will be different from the normal situation. Therefore, it is widely used in fault diagnosis. For example: fault diagnosis is performed by analyzing the time domain characteristics and frequency domain characteristics of vibration signals [14][15]. The temperature signal can also reflect the operating status of the motor, because many motor faults are caused by overheating and burning of the insulation layer. Such faults usually cause temperature abnormalities. Current and voltage signals are usually used for diagnosis of electrical fault types. For example, when a winding failure occurs, the current and voltage of the motor will be unbalanced.

In this study, the most representative vibration data was selected as the research basis for the fault diagnosis model. To collect the motor fault data, as shown in Figure 3, vibration signals in the axial and radial directions near the bearing were acquired using two single-axis acceleration vibration sensors. In this study, vibration signals were collected from a total of 37 grinding motors, including 20 normal motors and 17 faulty motors, forming a data set of vibration signals.

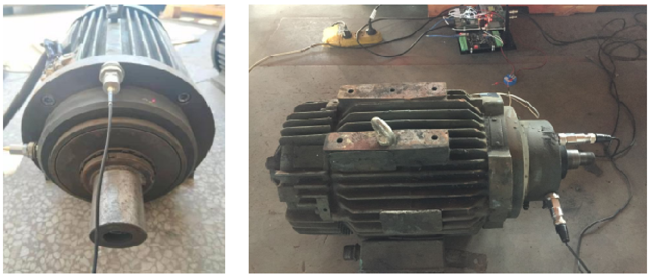

Fig. 3. Grinding Motor Data Collection

This paper presents an algorithm model for fault diagnosis based on convolutional neural networks (CNN). The structure of the model is illustrated in Figure 4. CNN models are commonly used for image recognition and classification, where convolutional and pooling layers are typically designed as two-dimensional modules. However, in the case of grinding motor vibration data, which is a one-dimensional acceleration signal, the two-dimensional modules in the model need to be transformed into one-dimensional modules. Furthermore, since vibration data is less complex than images, the number of layers in the original model is reduced to simplify the model and prevent overfitting during training, thus accelerating the training process.

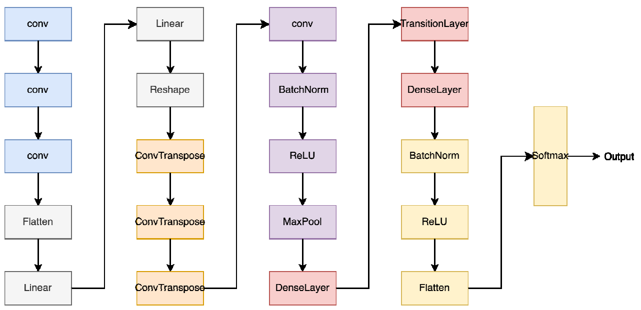

Fig. 4. Model Structure

The original data is initially encoded by a three-layer encoder composed of convolutional layers, resulting in a transformation from 2x1024 to 64x22. The output of the encoder is then flattened into a one-dimensional vector after passing through a Flatten layer. Subsequently, a fully connected layer is applied to produce a one-dimensional vector of 64 data. The output is further processed through Linear and Reshape operations, followed by three transpose convolutional layers in the decoder to generate the output while maintaining the same data structure as the input.

Next, the output data passes through a convolutional layer, followed by BatchNorm1d layer for batch normalization. After applying the ReLU activation function, the data undergoes feature compression through a max pooling layer. It then proceeds through a dense layer, which consists of four convolutional layers with dense connections. A transition layer is introduced to reduce the number of channels, comprising BatchNorm1d layer, a 1x1 convolutional kernel, and an average pooling layer. Subsequently, the data passes through another dense layer with the same structure before being outputted. The output is subjected to BatchNorm1d layer, ReLU activation function, and adaptive average pooling layer, and then flattened. Finally, the data is inputted into a Softmax classifier for classification. The key parameters of the model are listed in Table 1.

TABLE I. KEY PARAMETERS OF MODEL

Layer	*Parameters*
Conv1d	Input channel number is 2, output channel number is 16, Convolution kernel size is 22, stride is 6, padding is 6, activation function is ReLU
Conv1d	Input channel number is 16, output channel number is 32, Convolution kernel size is 10, stride is 4, padding is 4, activation function is ReLU
Conv1d	Input channel number is 32, output channel number is 64, Convolution kernel size is 5, stride is 2, padding is 2, activation function is ReLU
Flatten	64×22→1408
Linear	Input 1408, Output 64, activation function is ReLU
Linear	Input 64, Output 1408, activation function is ReLU
Reshape	1408→64×22
ConvTranspose1d	Input channel number is 64, output channel number is 32, Convolution kernel size is 5, stride is 2, padding is 2, activation function is ReLU
ConvTranspose1d	Input channel number is 32, output channel number is 16, Convolution kernel size is 10, stride is 4, padding is 4, activation function is ReLU
ConvTranspose1d	Input channel number is 16, output channel number is 2, Convolution kernel size is 20, stride is 6, padding is 6, activation function is ReLU
Conv1d	Input channel number is 2, output channel number is 64, Convolution kernel size is 7, stride is 2, padding is 3, activation function is ReLU
MaxPool1d	Convolution kernel size is 3, stride is 2, padding is 1
Dense Layer	The number of convolutional layers is 64, the number of input channels is 192, and the number of output channels is 64
Transition Layer	the number of input channels is 192, and the number of output channels is 96
Dense Layer	The number of convolutional layers is 4, the number of input channels is 96, and the number of output channels is 224
Softmax	Input 224, Output 2

In addition, in practical applications of grinding motor fault diagnosis, it is often encountered that fault categories not previously present in the old data set emerge. This situation can significantly impact the actual effectiveness of the model. Therefore, this study addresses this issue by expanding the output categories of the last Softmax layer, thereby reserving classification positions for future new fault categories and providing identification for new fault types. If the model encounters new fault categories during the engineering application process, the new fault categories are labeled with new identification markers in the data set. The model is then updated through transfer learning, thereby achieving automatic expansion of fault categories in the grinding motor fault diagnosis model.

IV. EXPERIMENTAL STUDY

To validate the effectiveness of the proposed model, vibration data was collected from 37 grinding motors with 12K sampling rate, comprising 20 functioning motors and 17 faulty motors. Each motor was sampled 100 times, each sample consists of two orthogonal vibration arrays, forming two channels data. Each channel consisted of 1024 data points. The waveform of data set is as Figure 5. The data set was divided into training and testing sets, using a ratio of 3:1, and utilized for model training.

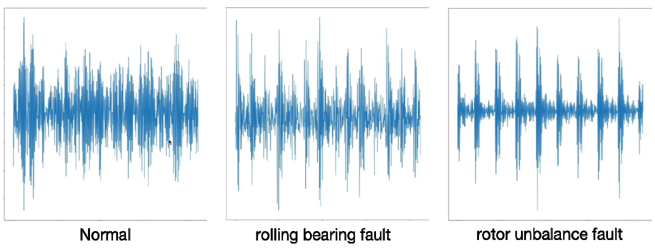

Fig. 5. Data Set Example

Additionally, Lenet [16], VGG [17], and ResNet [18] were selected as comparative models and trained using the same data set. The training loss functions of all models employed the cross-entropy loss function, and a total of 50 epochs were conducted. The results are illustrated in Figure 5. For the purpose of identification and distinction, the proposed model in this paper is referred to as DAENet.

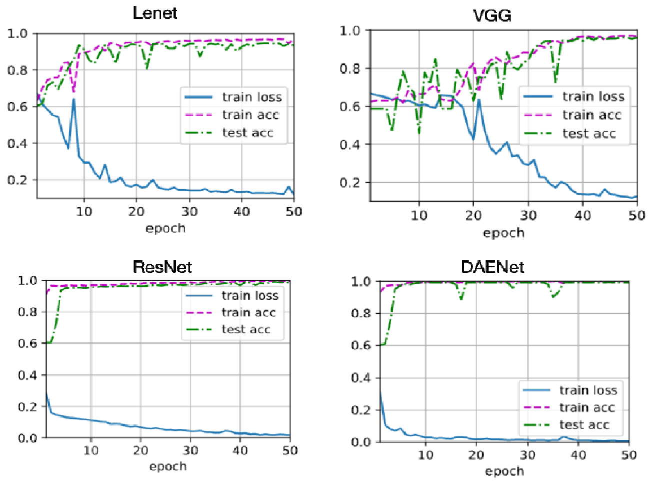

Fig. 6. Training results

TABLE II. TRAINING ACCURACY AND TEST ACCURACY

Model	*Training Accuracy*	*Test Accuracy*
Lenet	0.969231	0.933846
VGG	0.968301	0.962037
ResNet	0.994872	0.987692
DAENet	0.998974	0.988769

As Figure 6, the training of the Lenet, VGG, ResNet, and the proposed DAENet model all reached a convergent state, with the loss reduced to below 0.1. The final training accuracy and testing accuracy are presented in Table 2. By comparing the results, it is evident that both the ResNet model and the proposed DAENet model exhibit fault classification accuracy exceeding 99% on both the training and testing data sets, surpassing the accuracy of Lenet and VGG models. Furthermore, the proposed DAENet model demonstrates a faster convergence rate.

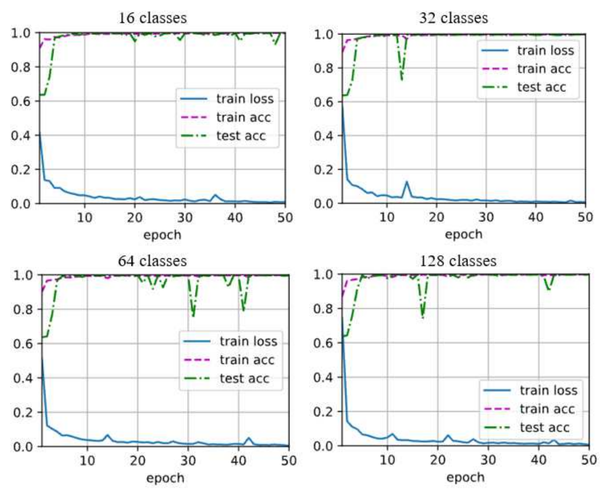

Fig. 7. Training results for different Softmax output

TABLE III. ACCURACY FOR DIFFERENT SOFTMAX OUTPUT

Model	*Training Accuracy*	*Test Accuracy*
16	0.997949	0.996923
32	0.997828	0.996713
64	0.999487	0.997924
128	0.998462	0.996923

In order to verify whether reserving multiple output bits for the Softmax layer will affect the model, the output of the Softmax layer was set to 16, 32, 64, and 128 respectively, and training and verification was performed on the original grinding motor vibration data set. Finally we got the training results are shown in Figure 7, and the respective training and testing accuracy are shown in Table 3.

From the training results and training accuracy, It can be seen that this strategy has basically no impact on the classification performance of the fault diagnosis model.

In order to validate the effectiveness of this algorithm in diagnosing motor faults across different motor types and batches, motor data from two different models and three maintenance batches were selected for model performance verification. The results are presented in the following table:

TABLE IV. ACCURACY FOR DIFFERENT MOTOR TYPES

Motor Type	*Specification*	*Repair Date*	*Test Accuracy*
HTT	256TY	2016.01	0.997632
HTT	256TY	2020.11	0.996934
SPENO	SSM132L/2	2017.11	0.997891

V. CONCLUSIONS

This study proposes a novel fault diagnosis model for grinding motors based on their characteristic failure patterns. To this end, a dedicated vibration signal acquisition system was designed and utilized to collect data from 20 functioning motors and 17 faulty motors. The collected data was carefully organized and employed for training the proposed fault diagnosis model.

The fault diagnosis model undergoes preprocessing steps, including data denoising and dimension reduction, using the principles of convolutional neural networks. Subsequently, the model performs fault classification and identification based on the processed vibration signal data.

To evaluate the performance of the proposed model, real-world collected data was utilized for training, and a comparative analysis was conducted against different convolutional neural network models, including Lenet, VGG, and ResNet, using the same data set of vibration data from grinding motors.

The results of the comparative analysis demonstrate that the proposed fault diagnosis model for grinding motors achieves an accuracy exceeding 99%, indicating a significantly higher precision in fault recognition compared to Lenet and VGG models, and slightly higher precision compared to ResNet. These findings highlight the advantages and superiority of the developed model in the domain of fault diagnosis for grinding motors.

Overall, this algorithm model, based on the modified CNN architecture, effectively addresses the challenge of fault diagnosis using vibration data, providing a more accurate and efficient approach for fault detection and classification.

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