INTELLIGENT FAULT DIAGNOSIS OF THE GEARBOX FOR A HIGH-PRECISION ROLLING MILL BASED ON THE MC2DCNN-LSTM MODEL

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Abstract – Addressing the complex structure of the rolling mill gearbox, challenges in fault signal identification, and the lack of clarity in fault location classification, a fault diagnosis method that fuses features from a multi-channel two-dimensional convolutional neural network (MC2DCNN) and a long short-term memory neural network (LSTM) is proposed. Furthermore, a three-channel hybrid coding two-dimensional sample structure is designed to achieve fault identification and classification, enabling adaptive classification of typical gearbox faults. This model integrates the vertical, horizontal, and axial vibration signals of the gearbox to construct the input sample, thereby encompassing more state information than traditional single-channel signals. Ultimately, fault identification and classification for gear and gearbox malfunctions are conducted using both an industrial test platform and existing experimental data. The results demonstrate that the model can accurately identify the typical faults of gearbox tooth surface wear, root cracks, broken teeth, and pitting on the tooth surface, achieving an accuracy of over 97%. In comparison to single-channel signals, the classification samples constructed through multi-channel signal hybrid coding significantly enhance the neural network's classification accuracy. A vast amount of industrial and experimental platform data verifies that the proposed intelligent diagnosis method outperforms traditional methods in terms of classification and recognition accuracy.

Keywords: Mill gearbox; Coupling model; Data classification; Intelligent diagnosis; Engineering data.

1. Introduction

As the core component of the high-precision rolling mill, the gearbox inevitably sustains various faults or damage during operating under complex and harsh conditions, including prolonged exposure to high speed, heavy load, and high temperature [1]. Due to the complexity of the rolling mill gearbox's service environment, the fault information of key components is often drowned out by strong noise, leading to a low signal-to-noise ratio in the collected gearbox vibration signal [2]. Furthermore, the intricate internal structure of the gearbox, coupled with the interconnected vibration response of each component and variable transmission paths, contributes to the lack of high diagnostic efficiency and accuracy in existing diagnostic methods [3]. The fault formation process frequently leads to the emergence of non-stationary phenomena, rendering existing technologies incapable of providing sufficient time between warning and failure to implement safety procedures. This often results in false alarms and unnecessary downtime for maintenance. To ensure the high efficiency and safe operation of the mill gearbox, it is imperative to accurately assess the gearbox's running state, implement predictive maintenance, and thereby guarantee the safe and stable operation of the entire equipment [4].

With the rapid advancement in computer and sensor technology, the fault diagnosis technology for the rolling mill gearboxes has gradually evolved to achieve automatic diagnosis. This, in turn, has led to the emergence of the theories of comparative analysis and fuzzy analysis. This evolution has significantly enhanced the efficiency and accuracy of fault detection in rolling mill gearboxes [5,6]. For example, Muralidharan et al. [7] employed fuzzy theory-based fault diagnosis technology for classification, successfully achieving feature extraction and automatic classification of centrifugal pump faults. However, while these methods theoretically achieved high diagnostic accuracy, they exhibited poor robustness and insufficient adaptability, making them impractical for complex conditions of large equipment [8]. Then, some algorithms, such as empirical mode decomposition, have been introduced, however, there are still some problems including limited self-adaptability, a large amount of calculation, and an imperfect mathematical theory, which cannot produce a set of stable and accurate gearbox fault diagnosis models [9–11]. At present, research on the intelligent diagnosis of gearbox faults includes acoustic emission detection, oil detection, current detection, and vibration detection [12]. Among these, vibration detection has emerged as the mainstream due to its advantages of convenience, reliability, and non-destructive testing. For example, Saxena et al. [13] captured the vibration signal of the gearbox using an acceleration sensor and constructed health indicators to complete the condition monitoring of the gearbox. McDonald et al. [14] proposed a method based on maximum correlation kurtosis deconvolution for detecting gearbox gear and bearing faults from vibration data, and proved that it performed well on computer equipment, demonstrating the feasibility of the method. Lei et al. [15-18] built fault diagnosis models for different parts of the gearbox based on gearbox transmission mechanisms and data simulation. They proposed a series of methods for vibration signal noise reduction, feature extraction, feature enhancement, and fault classification, addressing a significant number of problems in the field of gearbox fault diagnosis. Feng et al. [19-21] established vibration signal models for different parts of the gearbox under varying working conditions. They explained the frequency components and natural frequency offsets of each additional signal. They identified gearbox faults using algorithms such as empirical mode decomposition and adaptive multi-scale linear frequency modulation wavelet decomposition, and verified their feasibility through experiments.

With the increasing development of deep learning algorithms, scholars have harnessed the power of big data and deep learning to accomplish adaptive fault feature extraction and accurate state recognition, thereby greatly improving the fault diagnosis robustness of complex rolling mill gearbox equipment and overcoming the limitations of traditional methods [22]. For example, Hu et al. [23] proposed an intelligent fault diagnosis method for planetary gearbox fault diagnosis, which utilizes empirical mode decomposition and a deep convolutional neural network. This method achieved higher fault identification accuracy compared with the traditional particle swarm optimization neural network algorithm. Zare et al. [24] employed multi-channel convolutional neural networks to create fault databases for the purpose of wind turbine fault diagnosis. The obtained time-domain signals were depicted as time-frequency images for wind turbine fault diagnosis, greatly improving the diagnostic accuracy. Azamfar et al. [25] integrate multiple current signals and directly use them for classification, without manually extracting and analyzing fault features. This approach has certain advantages for the diagnosis of minor faults. Convolutional neural networks (CNNs) and CNN-based transfer learning have become important tools for accurate fault diagnosis of key parts of mechanical equipment due to their advantages of high computing speed and recognition accuracy [26-28].

In summary, the fault diagnosis of rotating machinery equipment, such as rolling mill gearboxes, typically follows two approaches: mechanism analysis and data-driven analysis. Mechanism analysis, a traditional method, primarily relies on mechanism modeling, simulation analysis, and other techniques to infer the precise location of a fault. This approach often hinges on the sound analysis of experienced technicians. Alternatively, data-driven analysis is an adaptive approach that leverages statistical data from signals like vibration, current, and temperature. It combines signal processing techniques such as time-domain, frequency-domain, and time-frequency domain analysis with neural network models. This method circumvents the need for manual intervention and exhibits immense potential in the realm of equipment fault diagnosis. Although a lot of achievements have been made in the existing research on gearbox fault diagnosis algorithms, theoretical models, feature extraction, and weak fault recognition, there are still few research results on the fault diagnosis of mill gearbox vibration signals due to the poor operating environment, complex structure, and strong noise interference. As a result, traditional pre-inspection and post-maintenance methods remain the primary approach in the rolling production process. Therefore, in this paper, a MC2DCNN model is proposed to realize fault classification for each component of a rolling mill gearbox. Additionally, the LSTM model is integrated to address the issue of gradient vanishing, which occurs when gradients explode in recurrent neural networks. Finally, using industrial and laboratory data, the accuracy of the fusion model is verified, thus completing intelligent fault diagnosis of rolling mill gearboxes from the perspectives of signal noise reduction, purification, and feature classification.

2. The Structure of the MC2DCNN-LSTM Model

In this section, the MC2DCNN model is designed to achieve fault classification for the key components of the rolling mill gearbox. The folding mode of vibration signals has been improved for input sample generation. Instead of generating input samples by simply cutting and folding single-channel signals, the vertical, horizontal, and axial vibration signals of the gearbox bearing seat are used as input samples. The vibration signals from these three directions are constructed into a two-dimensional sample data set containing three-channel information. The three-channel data undergo interleaved and differential line recombination to construct the input sample. This ensures that the data in the local receptive field can extract both the time sequence information of vibration signals in the horizontal direction and the vibration information in different directions simultaneously in the vertical direction, thereby improving the accuracy of fault classification. The structure of the MC2DCNN network model is shown in Figure 1.

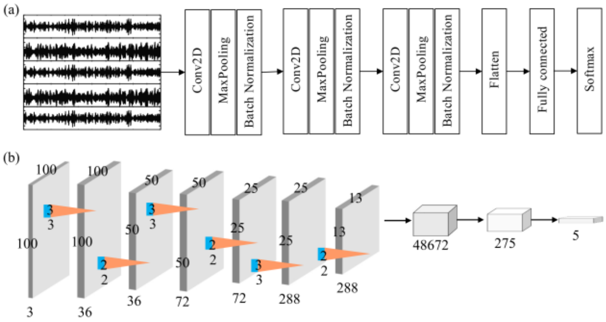

Figure 1: The Structure of the MC2DCNN Network Model

The CNN model is a type of feedforward neural network that incorporates convolutional computation. It is typically composed of a convolutional layer, a pooling layer, a fully connected layer, and an output layer. The purpose of the convolutional and pooling operations is to reduce the number of calculation parameters in the network model by sharing local receptive fields and weights, while decreasing the risk of overfitting and increasing calculation speed. The fully connected layer and the output layer then perform the feature classification task, similar to that of typical fully connected neural networks. The basic structure of a convolutional neural network is depicted in Figure 2.

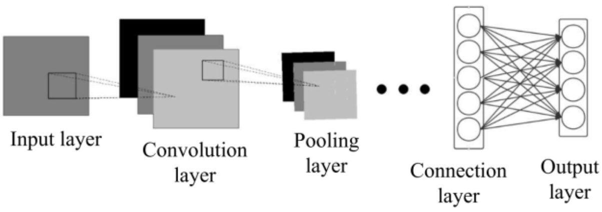

Figure 2: Structure of convolutional neural network

The design includes a convolutional neural network structure with a three-channel hybrid encoding approach, as illustrated in Figure 3. This approach generates sample data by interleaving the vibration signals from the horizontal, vertical, and axial directions at the bearing seat of the rolling mill gearbox. In this structure, the convolution kernel size is set to 3×3 to ensure that, as the convolution kernel traverses the input samples, it extracts the relationships within the time series of the vibration signals in the horizontal direction, while also capturing the relationships between the vibration signals in the vertical direction within the same temporal channel.

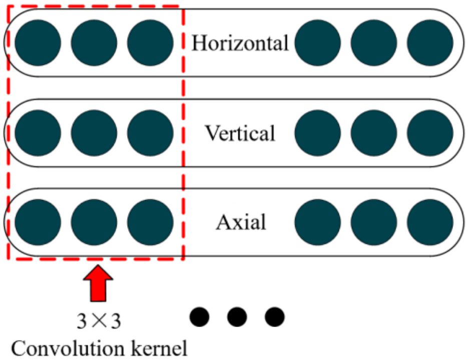

Figure 3: Three-channel hybrid encoding sample structure

The stride of the convolution kernel, when selected to be less than 3, will result in the local receptive field extracting information that comprises the first segment of the horizontal signal, the first segment of the vertical signal, and the second segment of the axial signal. This clearly does not meet the requirement of a 2D CNN model, which is to extract vibration information from different directions at the same instant for the rolling mill gearbox. To address this issue, a sample padding method, inspired by zero-padding, is proposed. This method utilizes zeros to separate each group of three-channel signals. The specific structure is illustrated in Figure 4.

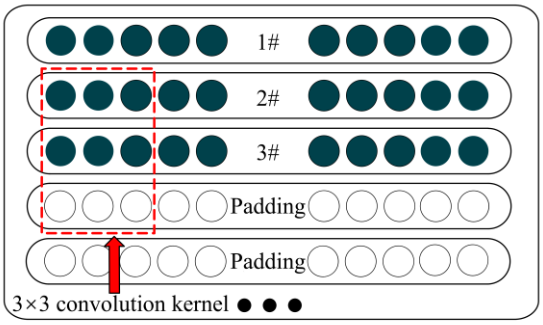

Figure 4: Three-channel Hybrid Padding Sample Structure

The proposed MC2DCNN model in this paper selects cross-entropy as the cost function to evaluate the error between the true values of the samples and the output results of the model. A Softmax linear output layer is employed to achieve the final classification of rolling mill gearbox faults. The Adam optimizer is utilized to update the parameters of the entire network until the predetermined training iterations are reached. The constructed convolutional neural network model comprises three sets of convolutional, pooling, and batch normalization layers, a fully connected layer, and a Softmax classifier. The training parameters and model structure parameters of each layer are presented in Tables 1 and 2.

Table 1. Training parameters of the MC2DCNN model

Parameter	Output feature scale
rate	0.001
Number of iterations	2600
Convolution kernel size	3×3
Depth of convolution kernel 1	36
Depth of convolution kernel 2	72
Depth of convolution kernel 3	288
The size of the sample core	2×2
Sample the step size of the nucleus	2

Table 2. Structural parameters of the MC2DCNN model

Network layer	Parameter	Output feature scale
Input layer	2D sample	100×100
Convolution layer 1	3×3 convolution nuclei with step size 1 (36)	36×100×100
Pooling layer 1	2×2 sampling kernel with step size 2	36×50×50
Convolution layer 2	3×3 convolution nuclei with step size 1 (72)	72×50×50
Pooling layer 2	2×2 sampling kernel with step size 2	72×50×50
Convolution layer 3	3×3 convolution nuclei with step size 1 (288)	288×25×25
Pool layer 3	2×2 sampling kernel with step size 2	288×13×13
Fully connected layer	Neuron	48672
Hidden layer	Neuron	275
Softmax classifier	Neuron	5

The 2DCNN model, based on horizontal, vertical, and axial three-channel samples of gearboxes, achieves a high accuracy in fault classification. However, this sample construction method still necessitates segmenting continuous signals, and the segmented signal fragments maintain temporal continuity. By integrating an LSTM model into the MC2DCNN model structure, issues such as gradient vanishing or gradient explosion, which are prone to occur in RNNs, are addressed through mechanisms like input/output gates and forget gates. The MC2DCNN-LSTM model utilizes the convolution and pooling operations of 2DCNN to reduce the dimensionality of features from the three-channel vibration signals of rolling mill gearboxes. These features are then fed into the LSTM network layer, and the final classification of rolling mill gearbox faults is completed using a Softmax linear output layer. Finally, the Adam optimizer is used to update the parameters of the entire network until the predetermined number of training iterations is reached, and cross-entropy is employed as the cost function to evaluate the error between the true sample values and the model's output results. The construction process of this model structure is depicted in Figure 5.

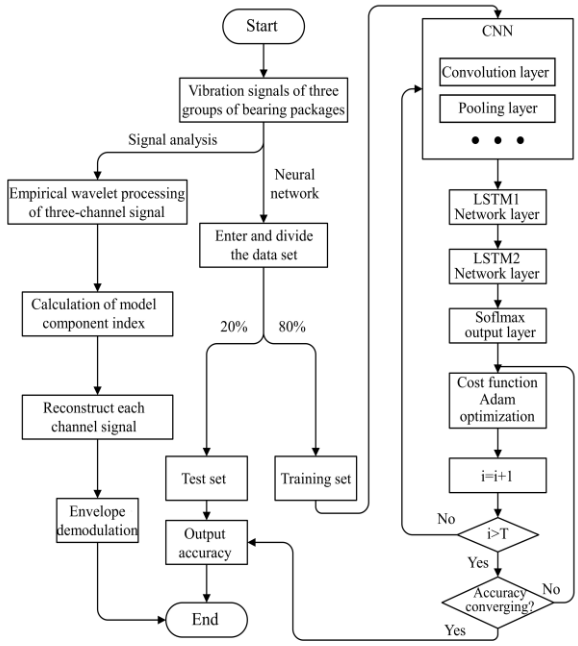

Figure 5: The construction process of MC2DCNN-LSTM model structure

The intelligent fault diagnosis of rolling mill gearboxes based on the MC2DCNN-LSTM model can be divided into four steps: acquisition and division of three-channel signals, structural design of the MC2DCNN-LSTM model, creation of input samples, and fault classification of rolling mill gearboxes using the MC2DCNN-LSTM model. The diagnosis process is illustrated in Figure 6.

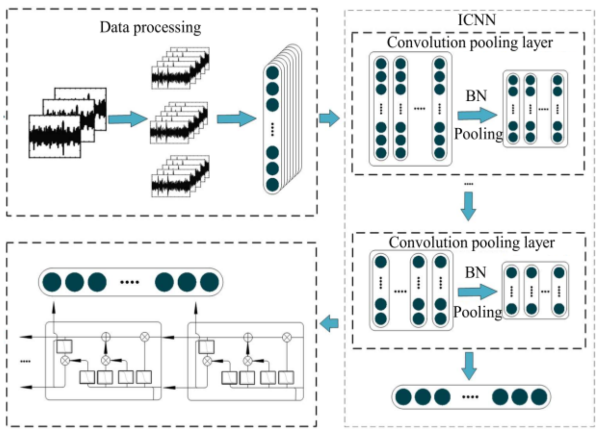

Figure 6: Diagnostic process

(1) Acquisition and Division of Three-Channel Signals: Acceleration sensors are used to acquire vibration signals from the horizontal, vertical, and axial directions of the rolling mill gearbox. An equal-length window is employed to segment and determine the signal length.

(2) Creation of Input Samples: The input samples are constructed using a three-channel mixed encoding sample structure, and a labelled sample dataset is created accordingly.

(3) Structural Design of the MC2DCNN-LSTM Model: The diagnostic model structure is shown in Figure 7. The model utilizes the cross-entropy loss function and the Adam optimizer for gradient descent. The LSTM2 regularization parameter is set to 0.0001, the initial learning rate is 0.01, the learning rate decay factor is 0.1, and the model undergoes 30 rounds of training with 40 iterations per round, totalling a maximum of 1200 iterations.

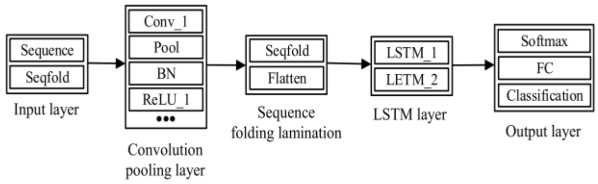

Figure 7: The construction process of MC2DCNN-LSTM model

3. Experimental Platform

3.1 Industrial Test Platform

To validate the effectiveness of the proposed fault diagnosis model in this paper, we collected vibration signals from the rolling mill gearbox in actual production for verification. The industrial experimental platform for rolling mill gearbox fault diagnosis is depicted in Figure 8. Utilizing gigabit Ethernet communication and switch expansion, a single computer can achieve parallel and synchronous testing and analysis of multi-channel dynamic signals. Alternatively, a USB 3.0 communication interface can be employed. This platform is capable of simultaneously collecting vertical, horizontal, and axial signals from the gearbox, and it permits the setting of test parameters. Based on the constructed dataset of three-channel mixed encoding samples from the gearbox's horizontal, vertical, and axial directions, the proposed algorithm in this paper was utilized to train and classify the samples. Similarly, continuous training was performed 10 times based on randomly dividing the dataset into training and testing sets.

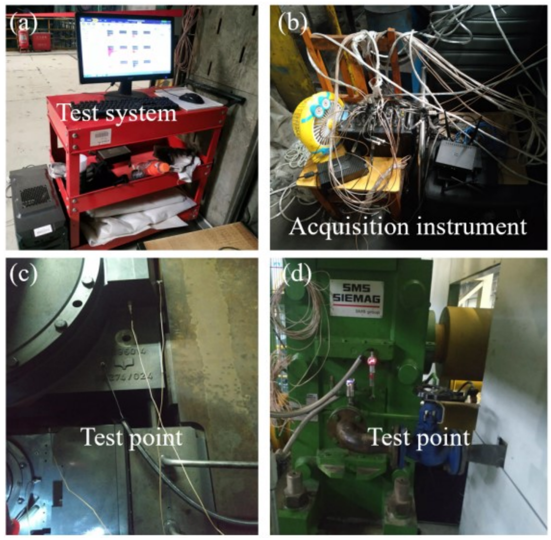

Figure 8: Industrial test bench for gearbox fault diagnosis of rolling mill. (a) Test system for industrial plat-form; (b) Acquisition instruments for industrial platform; (c) Distribution of measuring points on the gearbox; (d) Distribution of measuring points in three directions on the gearbox

3.2 Laboratory Test Platform

The failure of critical components in gearboxes does not occur only on gears; 20% of failures originate from the internal bearings. The failure modes of bearings mainly include the failure of the inner and outer rings, rolling elements, and cages. Therefore, to validate the effectiveness of the proposed algorithm model in diagnosing all types of gearbox faults, this section designs a classification experiment that incorporates common faults of gears and bearings. The experimental data come from the dynamic simulator of the transmission system at Southeast University [29], as shown in Figure 9. It includes eight types of fault data for bearings and gears, with each type consisting of eight signal sources. These signals originate from the motor, the horizontal, vertical, and axial directions of the planetary gearbox, the motor torque, and the vibration signals from the horizontal, vertical, and axial directions of the parallel gearbox. The system comprises a motor and a motor controller.

The sampling frequency of the sensors is 2000Hz, with 500 sets of samples for each fault type, including 9 fault types (including the normal state), totaling 4500 sets of samples. Among them, 3600 sets are used as training samples, and 900 sets are used as testing samples. On average, the training set for each fault state includes 400 sets of samples, and the testing set includes 100 sets of samples. Each sample contains three vibration signals from the horizontal, vertical, and axial directions of the gearbox under a certain state. Each signal segment contains 2000 sampling points, so each sample contains a total of 6000 sampling points and 4000 padding points.

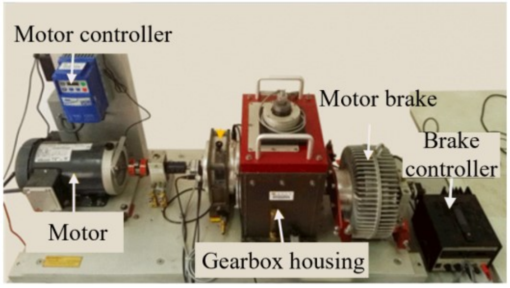

Figure 9: Experimental platform for gearbox total fault data

4 Results and Discussion

4.1 Analysis of Gear Fault Intelligent Diagnosis Results

Based on the constructed dataset featuring tri-channel hybrid encoded samples in the horizontal, vertical, and axial directions of the gearbox, the algorithm proposed in this paper was used to conduct training and classification experiments. Similarly, by randomly dividing the dataset into training and testing sets, 10 consecutive training sessions were conducted. The progress of one such training session is illustrated in Figure 10, and the accuracy rates for all 10 training and classification sessions are presented in Table 3.

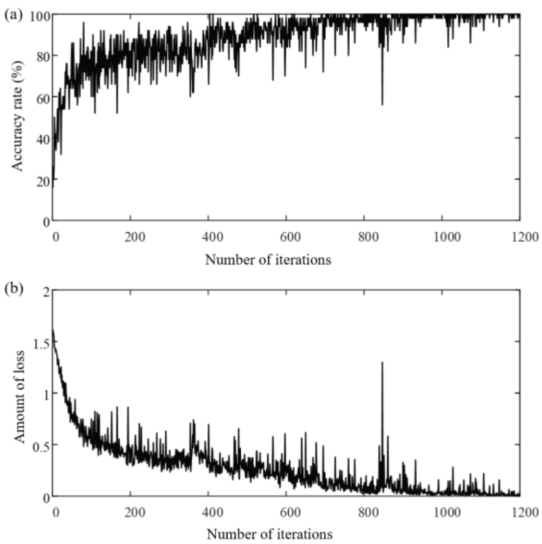

Figure 10: Model training progress. (a) Accuracy of the training set; (b) Loss of training set

Table 3. Accuracy of the training set

Test rounds	Accuracy rate
1	96%
2	98.6%
3	94.8%
4	96.8%
5	94%
6	94.4%
7	96%
8	95.8%
9	96%
10	97%

From the accuracy rates of the test set shown in Table 3, compared to the MC2DCNN fault diagnosis model, the proposed MC2DCNN-LSTM fault diagnosis model has improved the average accuracy of the test set from 93.0% to 95.94%. Ob-serving the confusion matrix generated by the model in Figure 11, although some samples of label 1 (gear tooth breakage) and label 3 (tooth root crack) are still the main form of misclassification, there is a significant improvement compared to the MC2DCNN model. This indicates that the fault classification ability of the MC2DCNN-LSTM neural network, which combines the temporal memory capabilities of LSTM with the powerful feature extraction abilities of 2DCNN, has been significantly enhanced compared to the MC2DCNN model. The accuracy rates of the 10 randomly trained test sets are shown in Figure 12.

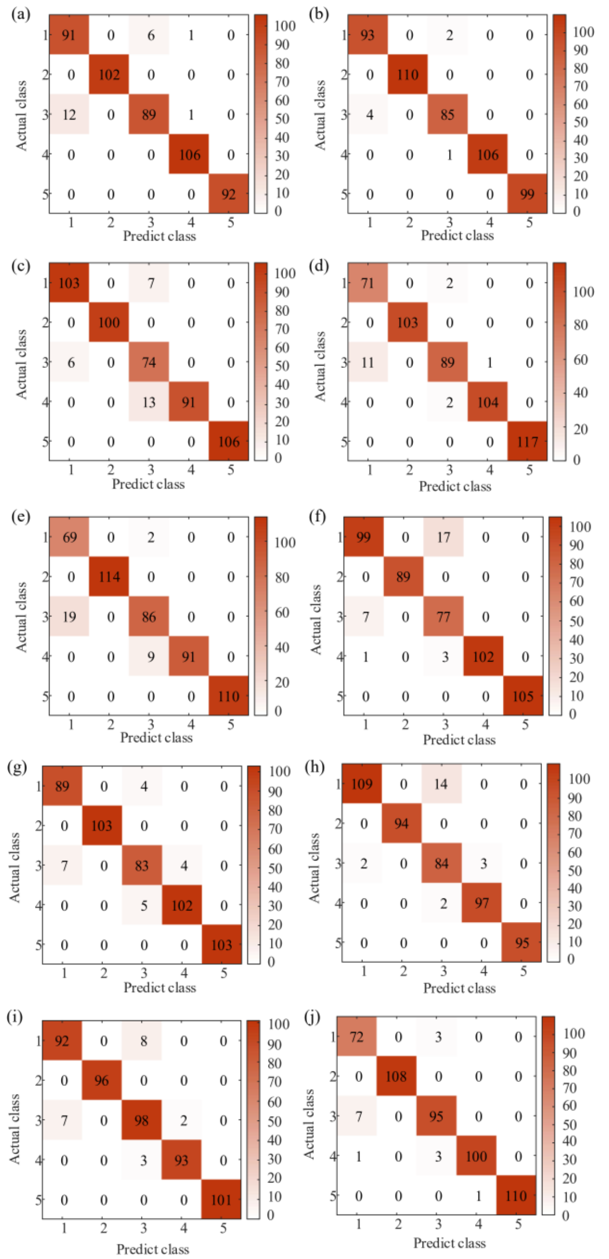

Figure 11: Confusion matrix of 10-round training test

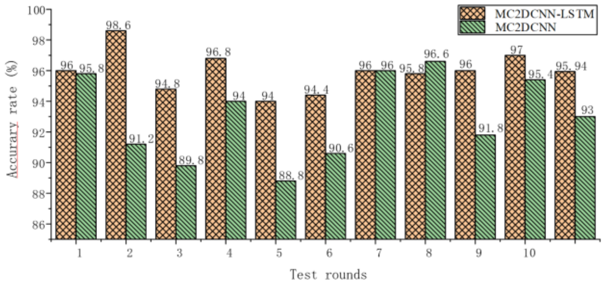

Figure 12: Comparison of test accuracy

To verify the advantage of the proposed MC2DCNN-LSTM neural network model in fault diagnosis accuracy, apart from the MC2DCNN model, a single-channel 2DCNN-LSTM model was also compared. While ensuring that the structure and parameters of the model were consistent with the MC2DCNN-LSTM model, the dataset samples were constructed solely by folding the vertical vibration signal sequence at the gearbox bearing seat into a 2D matrix. The training set and test set for this model were also randomly divided and run 10 times. The accuracy rates of the test set are shown in Table 4, and the confusion matrix of the classification results is presented in Figure 13.

Table 4. Accuracy of the training set

Test rounds	Accuracy rate
1	90.8%
2	93.2%
3	83.4%
4	85.2%
5	92.2%
6	87%
7	95%
8	92.4%
9	90.8%
10	92.2%

Based on the results of the test set accuracy, the model based on single-channel vibration signals exhibited a significantly lower average accuracy compared to the MC2DCNN-LSTM model that fused three-channel vibration signals. The average accuracy of the 10 tests was only 89.22%, and the test set accuracy varied significantly with different randomly divided training and test sets. This further proves that the classification performance of the neural network has been significantly improved after introducing the multi-channel mechanism. The comparison of the test set accuracy results of the three models is shown in Figure 14.

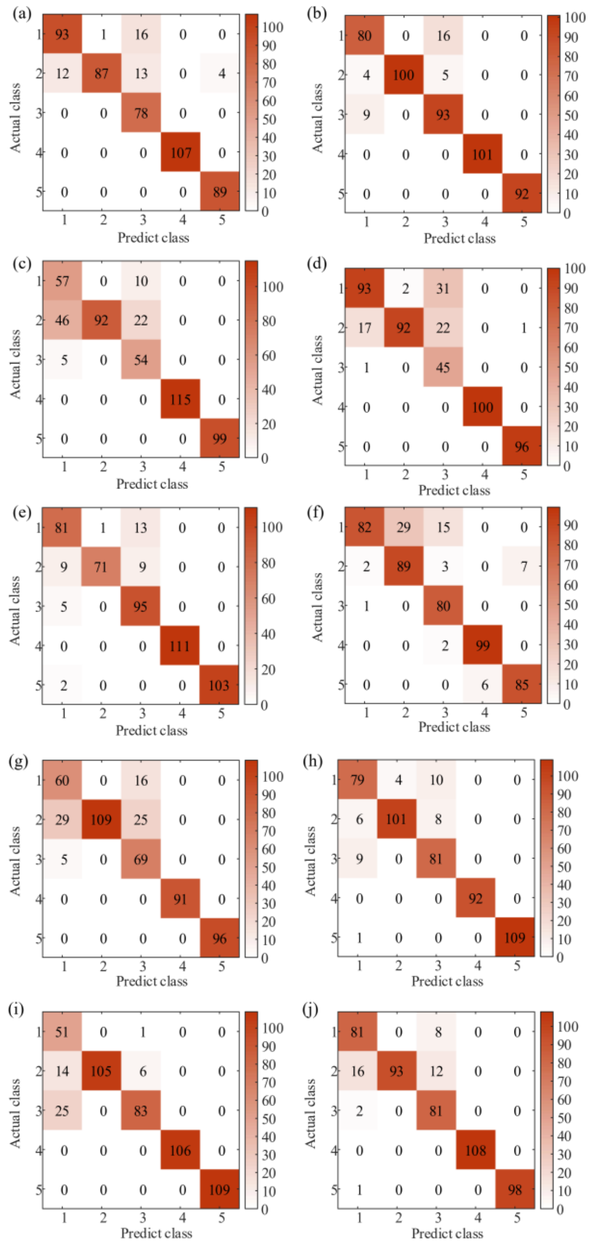

Figure 13: Confusion matrix of 10-round training test

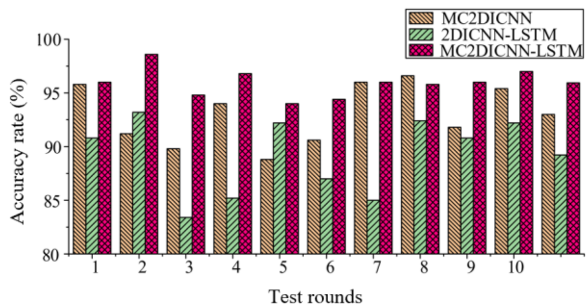

Figure 14: Accuracy rate of 10-round training test

By comparing the experiments between the MC2DCNN model and the MC2DCNN-LSTM model, it can be observed that the accuracy of the test set has been significantly improved after optimization with LSTM.

The MC2DCNN-LSTM model, compared to the MC2DCNN model, incorporates the temporal relationship of signals, enabling it to contain more fault information and extract effective information more comprehensively, thus achieving higher fault diagnosis accuracy. From the comparison between the 2DCNN-LSTM model and the MC2DCNN-LSTM model, it can be seen that the introduction of the multi-channel vibration signal convolutional sample structure in the MC2DCNN-LSTM model greatly increases the effective information of the samples and reduces the impact of single-channel interference information. This results in a significant increase in the average accuracy of the test set of the MC2DCNN-LSTM model compared to the 2DCNN-LSTM model.

4.2 Review Stage using IEEE Author Portal

The vibration signals of the gearbox in three directions: horizontal, vertical, and axial, are selected for this section. The division of the training set and test set as well as their corresponding labels are presented in Table 5. Figure 15 illustrates the vibration acceleration signals in the horizontal, vertical, and axial directions of a parallel gearbox under the condition of a tooth root crack.

Table 5. Gearbox data set

Fault type	Class tag
Bearing rolling element fault	1
Tooth surface wear	2
Bearing cage fault	3
Health state	4
Inner ring fault	5
Gear missing teeth fault	6
Outer ring fault	7
Root crack fault	8
Root pitting fault	9

The vibration signals are all structured into matrices according to a three-channel hybrid encoding method, where each matrix represents a labeled sample. A dataset is created by compiling all the sample signals, and the training set and test set are divided based on Table 5. The processed sample data is then input into the proposed model to validate the effectiveness of this method in gearbox fault diagnosis. The accuracy and loss during the model training process for the training set are shown in Figure 16.

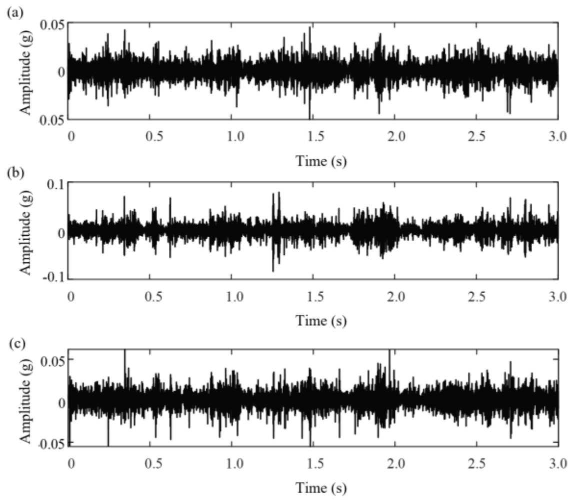

Figure 15: Time domain diagram of parallel gear box root cracks in three directions. (a) Horizontal direction; (b) Vertical direction; (c) Axial direction

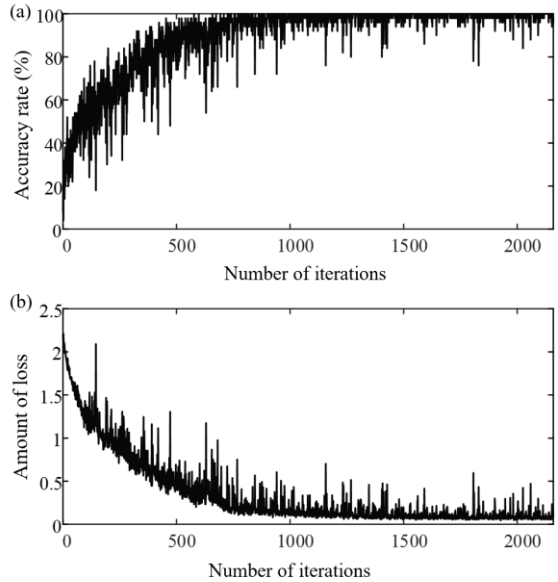

Figure 16: Model training progress. (a) Accuracy of the training set; (b) Loss of training set

To evaluate the generalization capability of the model, the trained model is used to diagnose and classify a test set consisting of 900 samples. The model's generalization capability is evaluated by its accuracy on the test set. After conducting two consecutive rounds of model training and test set identification, the results show that the recogni-tion accuracy of the first test model is 90.78%, while the second test model achieves 91.33% accuracy. As seen from the test set accuracy, the model still maintains an ac-curacy rate of over 90% in diagnosing nine failure modes (including normal conditions) that cover both gears and bearings, as illustrated in Figure 17. This demonstrates that the proposed model in this paper possesses high generalization capability.

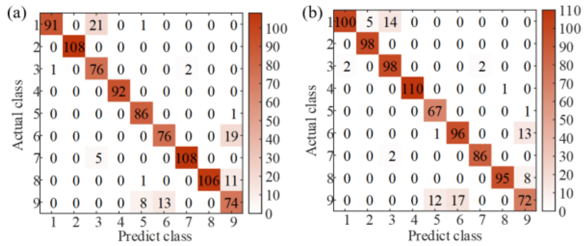

Figure 17: MC2DCNN-LSTM model matrix. (a) The first round of training tests the confusion matrix; (b) The second round of training tests the confusion matrix

The t-SNE dimensionality reduction was performed on the deep features extracted from the test set by the proposed model, and the scatter plot of the extracted deep features is shown in Figure 18. Among them, Figures (a)-(c) represent the feature scatter points output by partial activation layers, while Figure (d) depicts the feature scatter points output by the fully connected layer. It can be observed that the features of different states gradually cluster together during the transmission process within the model. The results indicate that the sample features extracted by the MC2DCNN-LSTM model have a larger distance between different categories of samples and a smaller distance between samples of the same category in the feature space. Fault samples exhibit a significant distribution difference in the feature space.

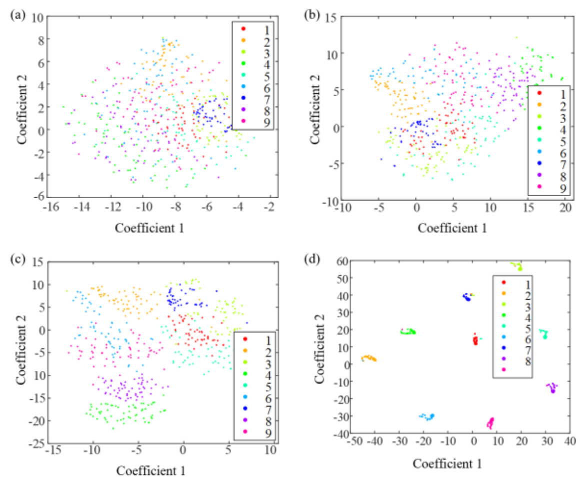

Figure 18: t-SNE feature visualization of test samples

4. Conclusions

As the core component of the rolling mill for stable rolling, the operating status of the rolling mill gearbox is crucial to the safe and stable operation of the entire equipment. To address the challenges posed by the difficulty in identifying fault signals and the unclear classification of fault locations in rolling mill gearboxes, a fault classification model integrating MC2DCNN and LSTM is proposed. Additionally, a two-dimensional sample structure featuring a three-channel mixed encoding method has been designed to facilitate fault identification and classification. Following algorithmic modeling and experimental validation, the conclusions drawn are as follows:

(1) The proposed two-dimensional data sample structure with three-channel mixed encoding integrates signal data from the vertical, horizontal, and axial directions of the gearbox. This structure contains more information about the gearbox's status compared to traditional single-channel signals. This method ensures that within the local receptive field, the data horizontally extracts temporal information of the vibration signal, while vertically extracting vibration information from different directions at the same moment.

(2) The proposed MC2DCNN-LSTM model achieves an accuracy rate of over 90% in identifying four common gearbox faults, including tooth surface wear, tooth root crack, tooth breakage, and tooth surface pitting. Experimental validation has demonstrated that this model possesses a higher diagnostic accuracy compared to traditional methods. Finally, through t-SNE dimensionality reduction visualization of each layer of the model, it is observed that the distance between different categories of extracted sample features in the feature space becomes larger, while the distance between samples of the same category becomes smaller, resulting in a significant difference in the distribution of fault samples within the feature space.

Acknowledgement

This work is supported by Hebei Province High-level Talent Funding Project [grant number: C20221029]; Hebei Province High-level Talent Funding Project [grant number: C20231128]; Hebei Provincial Higher Education Science and Technology Research Project [grant number: ZC2023140].

References

[1] Peng Y, Shi B. D, Liu C. Y, et al. Review on the integrated development of Equipment process Product Quality Control in Strip Rolling. Chinese Journal of Mechanical Engineering 2023, 59(20): 96-118. doi：https://10.3901/JME.2023.20.096.

[2] Wang H, Zhang R. L, Wu K. Gear box damage recognition model based on ICEEMDAN and IMWPE-LDA-BOA-SVM. Mechanical and Electrical

Engineering 2023, 40(11): 1709-1717. doi:https://10.3969/j.issn.1001-4551.2023.11.008.

[3] Ye Z, Yu J. B. Gear box Vibration signal Feature Extraction based on multi-channel weighted Convolutional neural Network. Chinese Journal of Mechanical Engineering 2021, 57(01): 110-120. doi：https://10.3901/JME.2021.01.110.

[4] Huang Q. X. Research progress on key equipment and technology of high-quality steel strip rolling. Chinese Journal of Mechanical Engineering 2023, 59(20): 34-63. doi：https://10.3901/ JME.2023.20.034.

[5] ShiH. T, Guo J, Bai X. T, et al. Gearbox incipient fault detection based on deep recursive dynamic principal component analysis. IEEE Access 2020, 8: 57646-57660. doi:https:// 10.1109/ACCESS.2020.2982213.

[6] He Z, Y, Shao H. D, Zhang H. Y, et al. Improved deep transfer auto-encoder for fault diagnosis of gearbox under variable working conditions with small training samples. IEEE Access 2019, 7: 115368-115377. DOI: 10.1109/ACCESS.2019.2936243.

[7] Muralidharan V, Sugumaran V, Indira V. Fault diagnosis of monoblock centrifugal pump using SVM. Engineering Science and Technology 2014, 17(3): 152-157. doi:https://10.1016/ j.jestch.2014.04.005.

[8] Yan Z, Tang B. P, Yan H, et al. Bearing performance degradation assessment based on time-frequency code features and SOM network. Measurement Science and Technology 2017, 28(4): 45-89. doi:https://10.1088/1361-6501/aa56c9.

[9] Huang N. E, Zheng S, Long S. R, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Mathematical, Physical, and Engineering Sciences 1998, 454(1971): 903-995. doi：https://10.1098/rspa.1998.0193.

[10] Li Y. B, Wang X. Z, Liu Z. B, et al. The entropy algorithm and its variants in the fault diagnosis of rotating machinery: A Review. IEEE Access 2018, 6: 66723-66741. doi:https:// 10.1109/ACCESS.2018.2873782.

[11] Han D. Y, Li G, Shi P. M. Research on coupling fault diagnosis method of rotating machinery based on EMD and fractal box dimension. Journal of Vibration and Shock 2013, 32(15): 209-214. doi: https://10.13465/j.cnki.jvs.2013.15.013.

[12] Lei Y. G, He Z. J, Lin J, et al. Research progress of Fault Diagnosis Technology for Planetary Gearbox. Chinese Journal of Mechanical Engineering 2011, 47(19): 59-67. DOI:10.3901/JME.2011.19.059.

[13] Saxena A, Ww B, Vachtsevanos G. A methodology for analyzing vibration data from planetary gear systems using complex Morlet wavelets. In, 2005[C]. IEEE, 2005. doi : https://10.1109/ACC.2005.1470743.

[14] Mcdonald G. L, Zhao Q, Zuo M. J. Maximum correlated Kurtosis deconvolution and application on gear tooth chip fault detection. Mechanical Systems and Signal Processing 2012, 33: 237-255. doi:https://10.1016/j.ymssp.2012.06.010.

[15] Lei Y. G, Jia F, Lin J, et al. An Intelligent Fault Diagnosis Method Using Unsupervised Feature Learning Towards Mechanical Big Data. IEEE transactions on industrial electronics 2016, 63(5): 3137-3147. doi：https://10.1109/TIE.2016.2519325.

[16] Lei Y. G, Lin J, Zuo M. J, et al. Condition monitoring and fault diagnosis of planetary gearboxes: A review. Measurement 2014, 48: 292-305. doi：https://10.1016/j.measurement.2013.11.012.

[17] Lei Y. G, Han D, Lin J, et al. Planetary gearbox fault diagnosis using an adaptive stochastic resonance method. Mechanical Systems and Signal Processing 2013, 38(1): 113-124. doi：https://10.1016/j.ymssp.2012.06.021.

[18] Lei Y. G, Lin J, He Z, et al. A review on empirical mode decomposition in fault diagnosis of rotating machinery. Mechanical Systems and Signal Processing 2013, 35(1): 108-126. doi : https://10.1016/j.ymssp.2012.09.015.

[19] Feng Z. P, Song X. P, Xue D. X, et al. Review on the Theory and Technology of Vibration Fault Diagnosis of Rotating Machinery. Journal of Vibration and Shock 2001, 20(4): 36-39. doi：https:// 10.13465/j.cnki.jvs.2001.04.010.

[20] Li K. Q, Feng Z. P. Application of Modal Parameter Recognition in Planetary Gear Box based on EMD and energy operator. Journal of Vibration and Shock 2018, 37(8): 1-8. doi：https://10.13465/i.cnki.ivs.2018.08.001.

[21] Chen X. W, Feng Z. P, Ming L. Fault Diagnosis of Planetary Gear Box under Time-varying Conditions Based on Iterative Generalized Synchronous Compression Transformation. Journal of Mechanical Engineering 2015(1): 131-137. doi：https://10.3901/JME.2015.01.131.

[22] Lei Y. G, Jia F, Zhou X, et al. Big data health monitoring method for mechanical equipment based on deep learning theory. Chinese Journal of Mechanical Engineering 2015, 51(21): 49-56. doi:https://10.3901/JME.2015.21.049.

[23] Hu N. Q, Chen H. P, Cheng Z, et al. Fault diagnosis method of planetary gear box based on empirical mode decomposition and deep convolutional neural network. Journal of Mechanical Engineering 2019, 55(07): 9-18. doi：https://10.3901/JME.2019.07.009.

[24] Zare S, Ayati M. Simultaneous fault diagnosis of wind turbine using multichannel convolutional neural networks. ISA Trans 2021, 108: 230-239. doi:https://10.1016/j.isatra.2020.08.021.

[25] Azamfar M, Singh J, Bravo I, et al. Multisensor data fusion for gearbox fault diagnosis using 2-D convolutional neural network and motor current signature analysis. Mechanical systems and signal processing 2020, 144: 106-861. doi:https://10.1016/j.ymssp.2020.106861.

[26] Ji J, Zhao C, Wang Y. Q. Fault diagnosis of rolling mill bearing roller and cage based on VMD-MMPE. Vibration. Test and Diagnosis 2023, 43(02): 290-297+409. doi ： https:// 10.16450/j.cnki.issn.1004-6801.2023.02.012.

[27] Sun Y, Zhang Z. M, Liu X. Y. Fault diagnosis method of fan gear box based on ResNet-ELM and transfer learning. Mechanical and Electrical Engineering 2023, 40(07): 978-987+1078. doi：https://10.3969/i.issn.1001 -4551.2023.07.002.

[28] Li X, Fu C. L, Lei Y. g, et al. Federated transfer learning method for equipment collaborative intelligent fault diagnosis to ensure data privacy. Chinese Journal of Mechanical Engineering 2023, 59(06):1-9.doi：https://10.3901/JME.2023.06.001.

[29] Shao S, Mcaleer S, Yan R, et al. Highly Accurate Machine Fault Diagnosis Using Deep Transfer Learning. IEEE transactions on industrial informatics 2019, 15(4): 2446-2455. doi ： https://10.1109/TII.2018.2864759.