

Intelligent Diagnosis Algorithm for Bearing Faults Based on Artificial Intelligence Deep Learning

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The performance and dependability of mechanical equipment have always been greatly impacted by bearing failure, which has long been a regular issue. The manual monitoring and analysis that is often required by the traditional Bearing Fault Diagnosis (abbreviated as BFD for convenience) procedures is inefficient and prone to error. In order to address this issue, this study examines the BFD method based on Artificial Intelligence (AI) Deep Learning (DL) and create a BFD model that maximizes BFD efficiency and accuracy by utilizing CNN-ETR (Convolutional Neural Networks-Extreme Randomized Trees Regression) under DL technology. The research results indicated that under the same other conditions, for three different types of faults, the diagnostic time of the experimental group was below 2.5 seconds, while the diagnostic time of the control group was between 2.5 seconds and 5 seconds. The diagnostic time of the experimental group was significantly lower than that of the control group, indicating a positive relationship between DL and the efficiency of the BFD algorithm.

Keywords: intelligent diagnosis algorithm for bearing faults; deep learning; artificial intelligence; diagnosis time; energy consumption

1. INTRODUCTION

The efficient operation of bearings is crucial for the performance and lifespan of mechanical equipment. However, due to harsh working conditions, prolonged load operation, and wear, bearings are prone to various failures such as fatigue rupture, ball detachment, and damage to the inner and outer rings. Traditional BFD methods usually rely on manual experience and professional knowledge, which have problems such as low diagnostic accuracy and efficiency. In recent years, AI-based DL technology has made significant progress in the field of fault diagnosis. The DL algorithm can automatically extract key features from a large amount of data through learning and training, and achieve accurate recognition and classification of complex fault issues. This study was conducted to examine BFD algorithms based on AI

and DL, and achieve the intelligent diagnosis (ID) of bearing faults (BF).

With the development of industrial production, BF has a serious impact on the reliability and safety of equipment. Therefore, it is essential to study the ID algorithm of BF for improving the maintenance efficiency and predictive maintenance of equipment. Xu et al. created a robot thin-walled BFD technique based on information fusion technology to accomplish intelligent bearing defect diagnostics. The findings of the study demonstrated that the accuracy of diagnosis was 1.7% higher when using neural network information fusion, and that the ID of thin-walled BF using self-organizing map neural network information fusion was 9.5% and 14.2% higher than that using vibration or acoustic emission signals alone [1]. An expert-system-based ID approach for BF was presented by Li et al. in response to the need for evaluating BF in RV (Rotary Vector) reducers and attaining ID of BF. Previous information and the foundation for identifying BF were coupled with

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feature data of different fault kinds that were collected from simulated real operating situations that were evaluated based on the characteristics of RV reducer bearings. The researchers increased the diagnostic accuracy of fault location and degree as well as the detection rate of BF kinds by developing an intelligent diagnostic expert system for RV reducer BF using Visual Studio software. According to the experimental data, the expert system performed well operationally, had the potential to perform much better [2]. For the key rotating component of printing equipment bearing, Hu et al. combined wavelet time-frequency analysis and inception model to propose an ID method for printing equipment BF, and built a printing equipment bearing experiment platform to verify the effectiveness of the proposed method. The experimental results showed that the average diagnostic accuracy of this method could reach 92.53%; compared with traditional intelligent diagnostic methods, the proposed method had certain advantages in diagnostic accuracy and stability, and could achieve high-precision BFD for printing equipment [3]. The above researches offered intelligent diagnostic methods for BF, but did not include a scientific method for verification.

In response to the above issues, the DL-based method is currently a research hotspot in this field in attempts to accurately identify micro faults in rolling bearings and achieve precise automation of the location, category, and severity of micro faults. Among them, due to the excessive reliance on the experience of technical personnel in traditional fault diagnosis methods, it is difficult to effectively obtain feature information from subtle faults. Gong et al. proposed a new method based on improved CNN-SVM (Convolutional Neural Networks-Support Vector Machine) and applied it to ID of motor support ball BF. The results showed that the improved CNN-SVM algorithm had a fault recognition accuracy of up to 99.86%. It had good migration generalization ability under different loads and offered practical engineering applications. Its diagnostic accuracy and testing time were significantly higher than those of other intelligent algorithms [4]. To solve the problem of low accuracy and stability of diagnostic results caused by the simple model of conventional fault diagnosis algorithms for certain bearings, Huang et al. proposed an intelligent diagnostic method based on DL. Their experiments showed that the average fault detection rate of the proposed method in practical applications could reach 99.7%, and it had great application value in equipment fault diagnosis in industrial production [5]. The aforementioned researches demonstrate the applicability of DL technology in the field of BFD, laying the foundation for combining it with intelligent BFD algorithms.

This current study focused on the ID algorithm for BF based on AI DL, explored the importance and current problems of BFD, and introduced the application of AI and DL in the field of fault diagnosis. This study emphasized its potential role in ID of BF, and focused on analyzing BFD algorithms based on DL. Finally, two algorithms were used to diagnose inner ring faults, outer ring faults, and ball faults. The relationship between DL and intelligent BFD algorithms was evaluated by comparing indicators such as accuracy, recall, F1 value, diagnostic time, and resource consumption.

2. ID ALGORITHM FOR BF BASED ON AI AND DL

2.1 BFD Methods

(1) Traditional BFD methods

The traditional BFD method was widely used before the emergence of AI DL algorithms [6–7]. It is based mainly on technologies such as signal processing, feature extraction, and pattern recognition. By collecting and analyzing vibration signals, sound signals, temperature signals, etc., of bearings, it identifies the type and degree of BF.

In time-domain analysis, the presence or absence of faults can be determined based on the characteristics of the bearing vibration signal waveform, amplitude, and peak. Frequency domain analysis converts the signal into a spectrogram and conducts fault diagnosis by observing the amplitude, frequency distribution, and other characteristics in the spectrogram. Time frequency domain analysis combines time-domain and frequency-domain methods to obtain more detailed signal features and improve diagnostic accuracy.

In addition to signal processing methods, there are also some commonly used feature extraction methods, such as maximum amplitude, root mean square, peak factor, etc., which can be calculated to determine whether there is a fault in the bearing. However, traditional BFD methods have several limitations and shortcomings. Firstly, traditional methods require the manual selection of suitable features for analysis, necessitating professional knowledge and experience, and is relatively cumbersome. Secondly, traditional methods are more sensitive to noise and interference, which may cause misjudgments or omissions. Finally, the accuracy and robustness of traditional methods for diagnosis are limited, and accurate judgments may not be possible for complex and ever-changing fault situations.

Traditional BFD methods can meet the needs of BFD to a certain extent, but they have several limitations [8–9]. With the development of AI and DL algorithms, their ID algorithms for BF are gradually emerging, with higher accuracy and robustness. Next, this study introduces an intelligent BFD method based on DL algorithm.

(2) Application of AI in BFD

With the rapid development of AI technology, its application in the field of BFD has become a research hotspot [10–11]. AI can perform DL on BF data, extract effective features, and use various Machine Learning (ML) algorithms for fault diagnosis.

AI technology can analyze and process a large amount of BF data to extract fault features. Through the use of DL network structures such as CNN and recurrent neural network, the vibration, temperature, sound and other sensor signals of bearings under different working conditions can be effectively learned, thus achieving the automatic identification and classification of BF.

AI technology can establish fault diagnosis models by learning a large number of bearing data samples, and apply them in real-time monitoring systems [12–13]. By using ML algorithms such as SVM and random forest, the BF can be accurately classified and predicted. In this way, not only can

faults be identified and judged in a timely manner after they occur, but also early warning can be given when the bearings are in a potential fault state, thereby avoiding equipment shutdown and the exacerbation of the fault [14–15].

2.2 DL Based BFD Algorithm

In recent years, research on BFD based on deep neural networks has achieved fruitful results, with CNN being the method most commonly used for BFD. Although the application of CNN eliminates the need for manual feature extraction and feature selection, it may lose features when the vibration signals of processing time series. If the original time series signals is converted into two-dimensional grayscale and then feature extraction is carried out, this issue would be addressed to a large extent. Therefore, this study combines ETR with CNN to design an adaptive BFD method based on ETR-CNN.

(1) Extreme random forest regression

ETR is a regression method which is an improved version of random forest. It introduces greater randomness when building decision trees, thus increasing the diversity of models. In ETR, the partition features and segmentation points of each decision tree are determined by random selection, rather than by the optimal segmentation points of features as in the traditional random forest. In addition, for each partitioning feature, ETR randomly selects a segmentation point instead of evaluating it using all possible segmentation points of that feature. Meanwhile, due to the introduction of greater randomness, the construction speed of ETR is relatively fast. ETR exhibits good performance in processing large-scale datasets and high-dimensional features, and is widely used in prediction and modeling tasks of regression problems [16–17].

It is assumed that the n dimensional sample is $A = (A_1, \dots, A_n)^U$ and variable H is the target variable of A . When H and A obey the joint probability distribution $Q_{AH}(A, H)$, to find a suitable objective function to evaluate the value of the variable, the prediction value of the minimum loss value can be quantified by calculating its minimum loss function. Assuming that the loss function is $Z(H, g(A))$, the expected value $R_{AH}(Z(H, g(A)))$ meets the minimum. Here, A and H represent the mathematical expectation of A and H joint probability distribution.

Similarly, the loss function $Z(H, g(A))$ represents the similarity between the predicted value $g(A)$ and the true unknown value H . Assuming that the prediction algorithm performs well, the predicted values of $g(A)$ and H are relatively close. At this point, $Z(H, g(A))$ approaches 0; otherwise, it would approach 1. Therefore, in the classification problem, the similarity between the predicted values $g(A)$ and H can also be used for discrimination. If the same, the loss is 0; otherwise, the loss is 1. It can be expressed as follows:

$$Z(H, g(A)) = O(H \neq g(A)) = \begin{cases} 0 & H = g(A) \\ 1 & \text{otherwise} \end{cases} \quad (1)$$

According to the above derivation, the expected value of $R_{AH}(Z(H, g(A)))$ can be obtained with the minimum mean

square error method. In the regression problem, $g(a) = R(H|A = a)$ can be obtained; In classification problems, if t is used to represent the category obtained by H , $g(a) = \operatorname{argmax}_{h \in t} Q(H = h|A = a)$.

In the ETR classification model, assuming that limit tree g consists of n decision trees: $j_1(a), \dots, j_n(a)$. In the classification problem, $g(a)$ can be represented as follows:

$$g(a) = \operatorname{argmax}_{h \in t} \sum_{k=1}^K O(h = j_k(a)) \quad (2)$$

(2) Signal-grayscale conversion

In this study, the signal was converted into pixels with data between [0255], which can effectively prevent the impact of large differences between signals collected by different sensors on the diagnosis results; subsequently, data augmentation was used to expand the limited fault data, reducing the risk of overfitting in the model. Processing data can be represented as follows:

$$Q(q, m) = \operatorname{round} \left(\frac{a_o - a_{\min}}{a_{\max} - a_{\min}} * 255 \right) \quad (3)$$

where Q is the converted pixel signal and $\operatorname{round}()$ is the floor and ceiling functions. Among them, a_o is the o th sampling point of the data, and a_{\max} and a_{\min} represent the maximum and minimum values of the data, respectively.

(3) A BFD model based on CNN-ETR

To verify the effectiveness of the CNN-ETR diagnostic model proposed in this study, a bearing experimental platform was used for corresponding experimental data collection. Figure 1 shows the experimental device. Three types of faults were selected. Based on practical experience in analyzing vibration signals of rotating machinery equipment on industrial sites, to fully reflect the actual operating status of rotating machinery equipment, at least 5–7 revolutions of vibration timing signals are required for analysis. In this study, when the speed of the motor was 1500r/min under no load and the sampling frequency was 5K, the determined sampling length was about (1000–1400). To ensure the reliability of fault data, the sample length for various types of faults was set to 1024 vibration data points.

(4) CNN-ETR parameter selection

In the CNN-ETR modeling process, the selection of model parameters is a key factor determining its performance. Appropriate parameters not only can improve its recognition rate; they can also significantly reduce its training time. Therefore, in this study, several important super parameters in the CNN-ETR model were selected: activation function, optimizer type and its learning rate, and batch processing sample number. To ensure the consistency of experimental results, the following experiments all used ten cross-validation methods, and ultimately selected diagnostic accuracy in the test set, diagnostic time of the model, etc., as evaluation indicators.

To further evaluate the effectiveness of the CNN-ETR model in intelligent fault diagnosis of bearings, the performance of the CNN-ETR algorithm is evaluated here by citing evaluation indicators widely used in ML. Specifically, it refers to accuracy, recall, and F1 indicators. They are represented as follows:

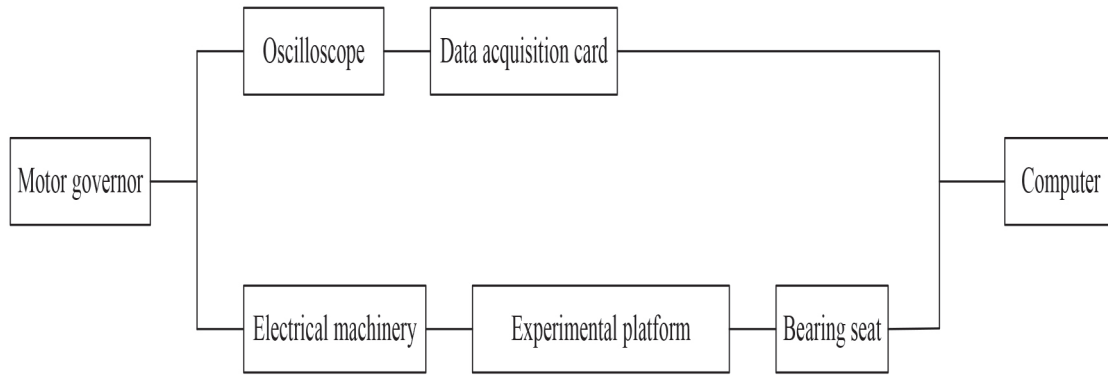


Figure 1 Experimental setup diagram of the bearing experimental platform.

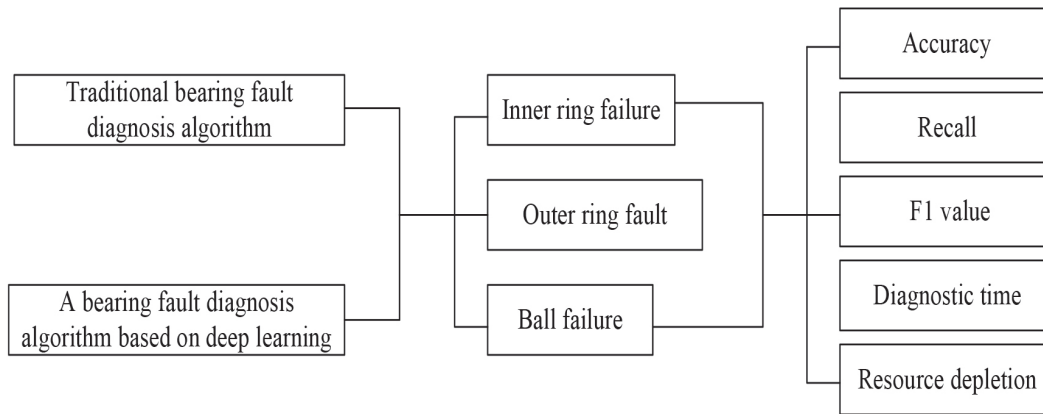


Figure 2 Introduction to the experimental process.

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1 = \frac{2TP}{2TP + FP + FN} \tag{6}$$

$TP + FP + FN + TN$ is the total of all samples. TP refers to the actual sample type being positive, and the predicted type being also positive; TN indicates that the actual sample type is inverse, and the predicted type is also inverse; FN refers to the actual sample type being positive, while the predicted type is negative; FP refers to the actual sample type being negative, while the predicted type is positive.

3. EXPERIMENT AND EVALUATION OF ID ALGORITHM FOR BF

3.1 Experimental Setup and Dataset

- (1) Data collection: Firstly, a large amount of bearing vibration data needs to be collected and annotated. The dataset should include samples of normal operation and different types of fault samples. In this study, the dataset was divided into training and testing sets, and cross validation was used to evaluate the performance of the algorithm.
- (2) Algorithm selection: A DL based BFD algorithm was selected as the benchmark algorithm. This algorithm used as a comparative algorithm for experimentation.

- (3) Experimental group and control group: A BFD algorithm based on DL was used for the experimental group used, while the BFD algorithms were applied to the control group.
- (4) Feature extraction: Each sample in the dataset was feature-extracted for input into DL and control algorithms.
- (5) Model training: The training set data was used to train the BFD algorithm based on DL, the super parameters were adjusted, and the cross-validation method was used for model selection. The control group algorithm also underwent corresponding training and parameter adjustments.
- (6) Experimental evaluation: The reserved test dataset was used to evaluate the trained DL model. The accuracy, recall, F1 value, diagnostic time, and resource consumption of the model on the test dataset were calculated to evaluate the performance and effectiveness of the algorithm. Figure 2 shows the experimental process:

3.2 Evaluation of Experimental Results

This article divided the dataset into a training set and a testing set (with a ratio of 7:3), and constructed models using DL-based BFD algorithms and traditional ML algorithms for training. Using the testing set data, the two models were evaluated and compared with manually annotated real fault data. The accuracy, recall, and F1 values of inner ring faults, outer ring faults, and ball faults were calculated, and the above experimental process was repeated. A total of ten sets of experiments were conducted to ensure consistent experimental results.

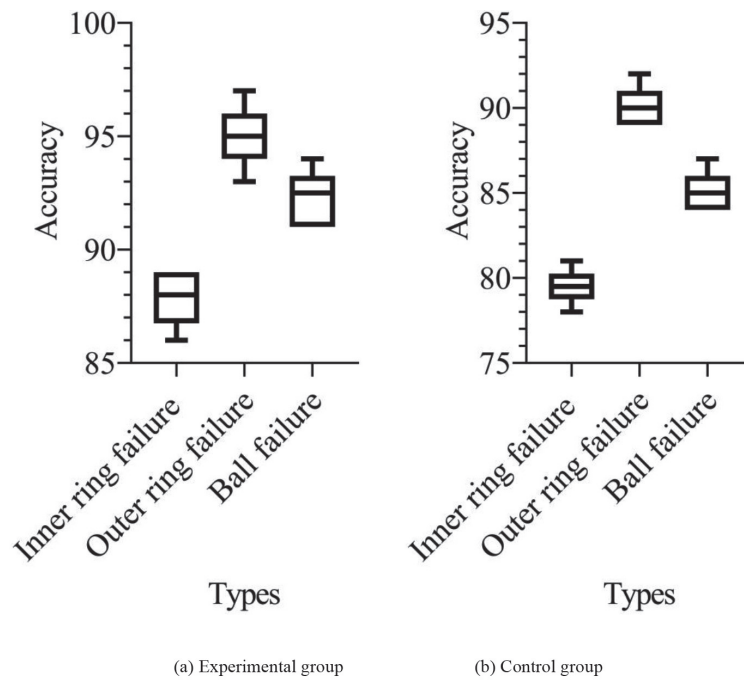


Figure 3 Accuracy of two sets of algorithms for inner ring faults, outer ring faults, and ball faults.

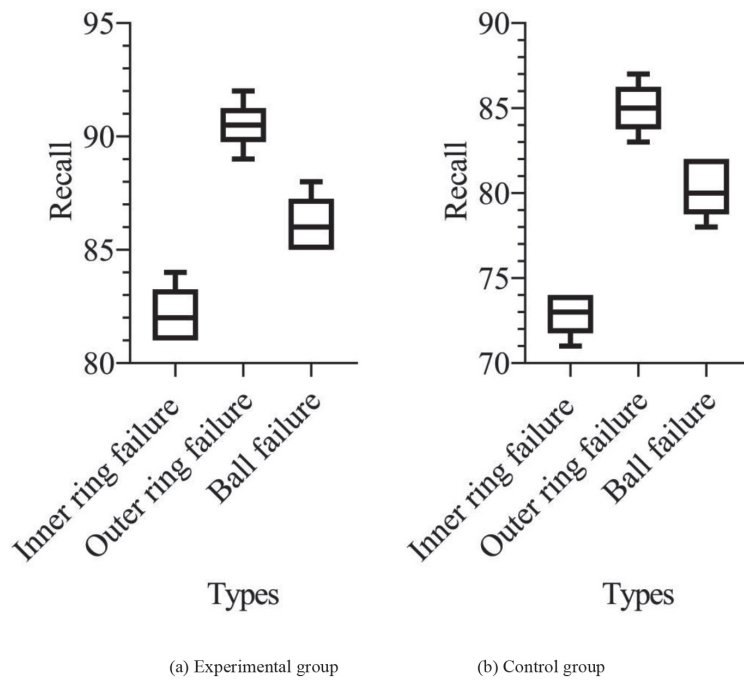


Figure 4 Recall rates of two sets of algorithms for inner ring faults, outer ring faults, and ball faults.

(1) Accuracy

Accuracy refers to the number of samples correctly classified by the classifier. This study applied two sets of algorithms for inner ring faults, outer ring faults, and ball faults. Figure 3 shows their accuracy:

In Figure 3(a), in the experimental group, the accuracy of inner ring faults is between 85%–90%, the accuracy of outer ring faults is between 92%–98%, and the accuracy of ball faults is between 90%–95%; in Figure 3 (b), in the control group, the accuracy of inner ring faults is between 77%–82%, the accuracy of outer ring faults is between 88%–93%, and the accuracy of ball faults is between 83%–88%;

in Figure 3, for three different types of faults, the accuracy of the experimental group is significantly higher than that of the control group, indicating that DL could improve the classification performance of BFD algorithms.

(2) Recall rate

The recall rate measures the proportion of positive samples correctly detected by the classifier, where a higher value indicates that the algorithm has stronger recognition ability for positive samples. This study identified inner ring faults, outer ring faults, and ball faults using two sets of algorithms. Figure 4 shows their recall rates:

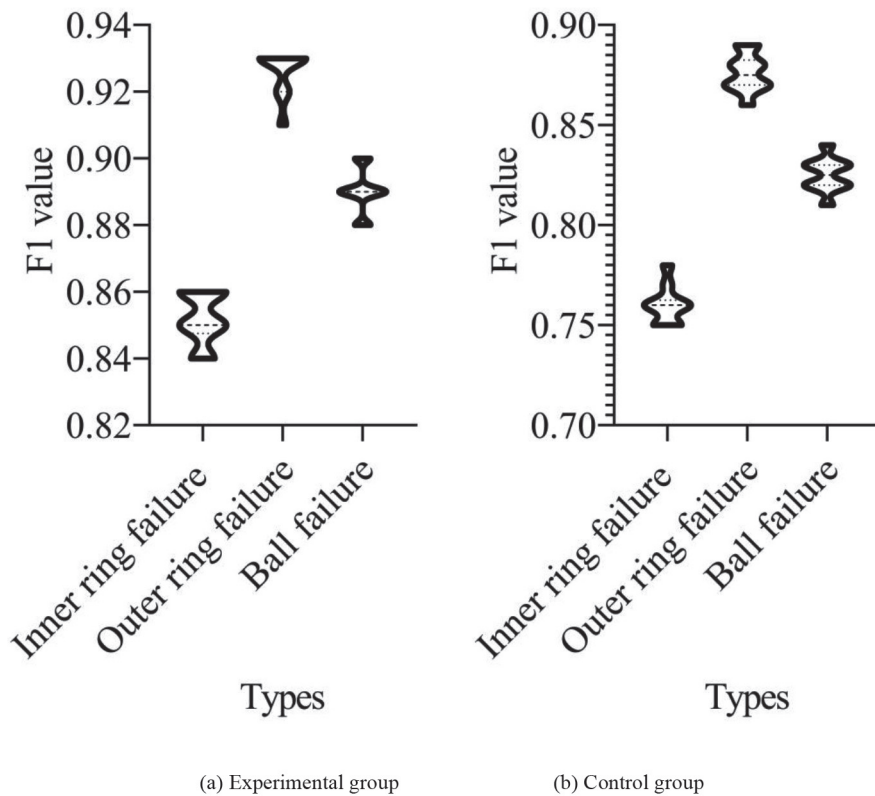


Figure 5 F1 values of two sets of algorithms for inner ring fault, outer ring fault, and ball fault.

In Figure 4(a), in the experimental group, the recall rate for inner ring faults is between 80%–85%, the recall rate for outer ring faults is between 88%–93%, and the recall rate for ball faults is between 84%–89%; in Figure 4 (b), in the control group, the recall rate for inner ring faults is between 70%–75%, the recall rate for outer ring faults is between 82%–88%, and the recall rate for ball faults is between 77%–83%; in Figure 4, for three different types of faults, the recall rate of the experimental group is also significantly higher than that of the control group, indicating that DL could improve the recognition ability of BFD algorithms.

(3) F1 value

The F1 value takes into account both accuracy and recall, and is a comprehensive indicator when evaluating the performance of classifiers. The higher the value, the better the algorithm performs in terms of balancing accuracy and recall. This study calculated the F1 values of two sets of algorithms for testing inner ring faults, outer ring faults, and ball faults. Figure 5 shows the result:

In Figure 5(a), in the experimental group, the F1 values for the inner ring fault are between 0.83 and 0.87, the F1 values for the outer ring fault are between 0.9 and 0.94, and the F1 values for the ball fault are between 0.87 and 0.91; in Figure 5 (b), in the control group, the F1 values for inner ring faults range from 0.74 to 0.79, outer ring faults range from 0.85 to 0.9, and ball faults range from 0.8 to 0.85; in Figure 5, for three different types of faults, the F1 value of the experimental group is higher than that of the control group, indicating that DL could improve the recognition ability of BFD algorithms.

(4) Diagnosis time

In terms of ID of BF, the length of time for diagnosis depends on the algorithm used and the speed of data

processing. When the data sorting speed is the same, the quality of the algorithm determines the speed of diagnosis time. Therefore, this study calculated the diagnosis time of two sets of algorithms for inner ring faults, outer ring faults, and ball faults. Figure 6 shows the results:

In Figure 6(a), the diagnostic time of the experimental group for inner ring faults is between 1.5s and 2s, the diagnostic time for outer ring faults is between 2s and 2.5s, and the diagnostic time for ball faults is between 1s and 1.5s; in Figure 6(b), in the control group, the diagnosis time for inner ring faults is between 3s–3.5 seconds, the diagnosis time for outer ring faults is between 4.5s–5 seconds, and the diagnosis time for ball faults is between 2.5s–3 seconds; in Figure 6, for three different types of faults, the diagnostic time of the experimental group is below 2.5s, while the diagnostic time of the control group is between 2.5s and 5s, indicating that DL could improve the efficiency of the BFD algorithm.

(5) Resource consumption

This study compared the computational resource consumption of two sets of algorithms on the same hardware device, and calculated the CPU (Central Processing Unit) usage rate and GPU (Graphic Processing Unit) memory usage. Figures 7 and 8 show the results:

In Figure 7 (a), the CPU utilization rate for inner ring faults in the experimental group is between 2.5%–3%, the CPU utilization rate for outer ring faults is between 4.5%–5%, and the CPU utilization rate for ball faults is between 3%–3.5%; in Figure 7 (b), in the control group, the CPU utilization rate for inner ring faults is between 7%–7.5%, the CPU utilization rate for outer ring faults is between 13%–13.6%, and the CPU utilization rate for ball faults is between 10.5%–11%; in Figure 7, for three different types of faults,

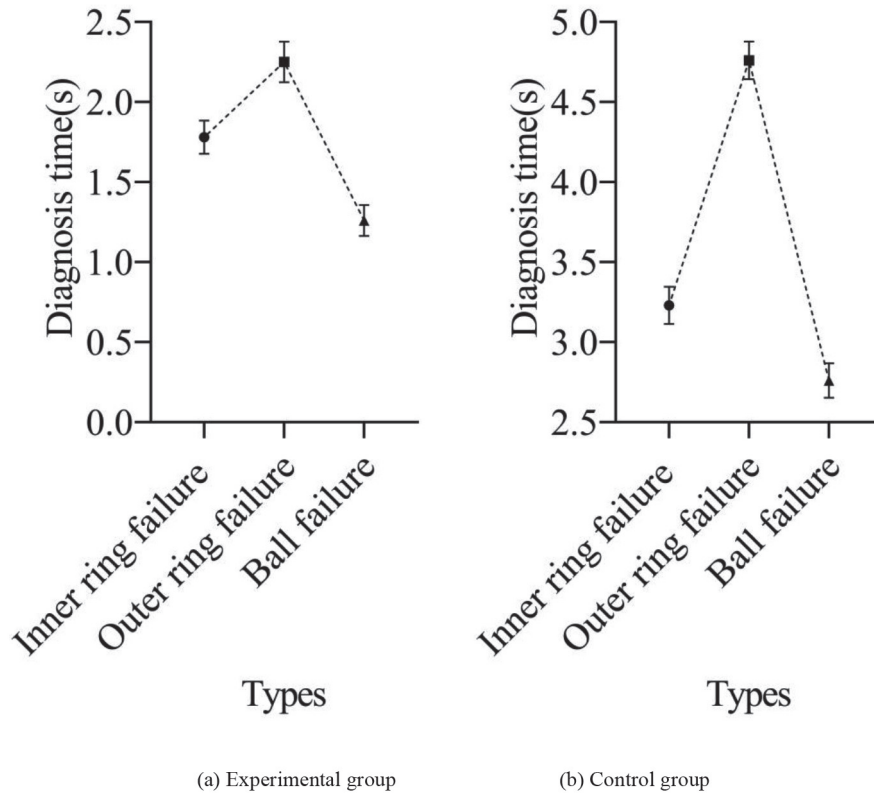


Figure 6 Diagnosis time of two sets of algorithms for inner ring faults, outer ring faults, and ball faults.

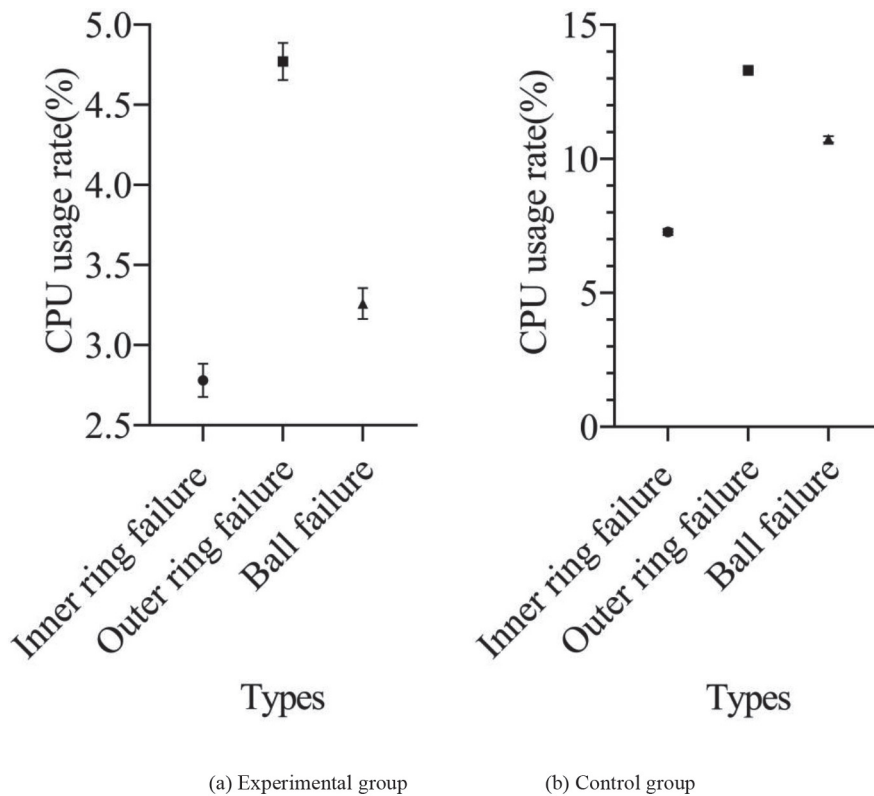


Figure 7 CPU usage rates for diagnosing inner ring faults, outer ring faults, and ball faults using two sets of algorithms.

the CPU utilization rate of the experimental group remained below 5%, while the CPU utilization rate of the control group is between 7%–13.6%, indicating that DL could reduce the resource consumption of BFD algorithms.

In Figure 8(a), the experimental group’s GPU memory usage for inner circle faults ranges from 1.2GB to 1.7GB. The GPU memory occupied by the outer ring fault is between 2GB–2.5GB, and the GPU memory occupied by the ball fault

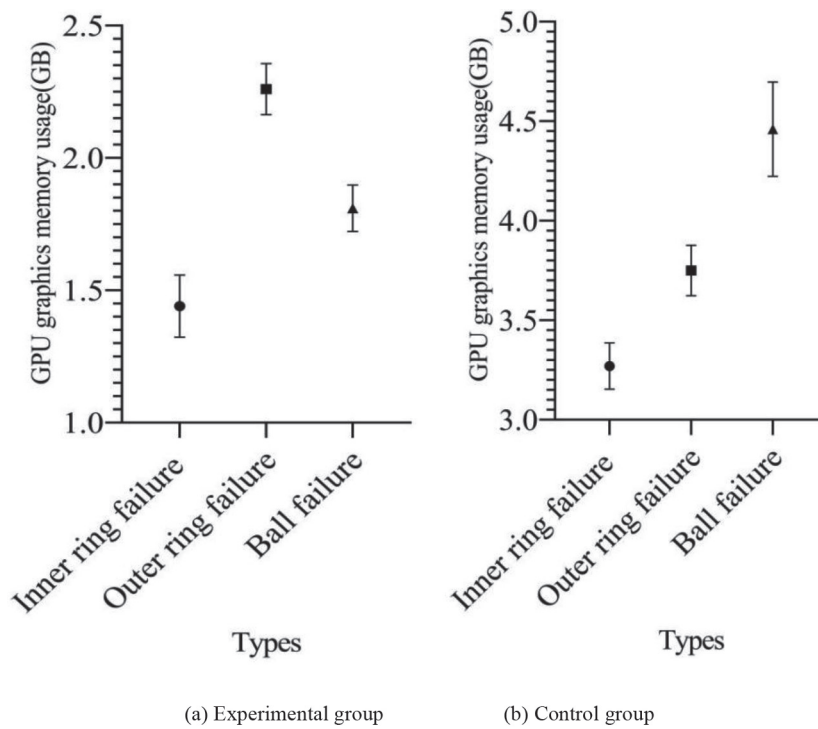


Figure 8 GPU memory usage for diagnosing inner ring faults, outer ring faults, and ball faults using two sets of algorithms.

is between 1.6GB–2GB; in Figure 8(b), in the control group, the GPU memory occupied by the inner ring fault is between 3GB–3.5GB, the GPU memory occupied by the outer ring fault is between 3.5GB–4GB, and the GPU memory occupied by the ball fault is between 4GB–4.9GB; in Figure 8, for three different types of faults, the GPU memory occupation of the experimental group remains below 2.5GB, while the GPU memory occupation of the control group is between 3GB–4.9GB, further indicating that DL could reduce the resource consumption of BFD algorithms.

4. CONCLUSIONS

This study explored the ID algorithm for BF based on DL, and constructed a CNN-ETR BFD model using DL technology, achieving accurate identification and prediction of BF. To verify the relationship between DL and intelligent diagnostic algorithms for BF, this study compared the accuracy, recall, accuracy, diagnostic time, and energy consumption of two sets of algorithms for inner ring faults, outer ring faults, and ball faults. The BFD algorithm based on DL performed much better than traditional BFD algorithms for these three types of faults, indicating that DL could improve the performance of BFD algorithms, enhance the accuracy and reliability of BFD, and provide better support and guidance for practical applications, thereby offering a reliable theoretical basis for the application of this algorithm in practical engineering.

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