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MECHANICAL BEARING FAULT DETECTION BASED ON TWO-STAGE NEURAL NETWORK

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Bearing is one of the key components widely used in mechanical equipment. Due to overload, fatigue, wear, corrosion and other reasons, bearings are easily damaged during machine operation. Therefore, the monitoring and analysis of the bearing state is very important. It can find the early weak fault of the bearing and prevent the loss caused by the fault. This paper proposes a long-term and short-term network combining the lightweight convolutional block attention module (CBAM-LSTM). In the field of bearing fault detection, the experimental results show that the CBAM-LSTM method can accurately identify a variety of mechanical bearing faults with an accuracy of 99,13 7 %.

Keywords: bearing fault detection, rotating vibration, neural network, CBAM-LSTM

INTRODUCTION

In fact, more than 50 % of rotating machine failures are related to bearing failures. Rolling bearing failure may lead to severe shaking of equipment, equipment shutdown, stop production, and even cause casualties. In general, early weak bearing failures are complex and difficult to detect. Recently, bearing fault detection and diagnosis has been concerned. Vibration signal analysis is one of the most important and useful tools in all types of bearing fault diagnosis methods. The greater the bearing wear, the greater the vibration signal, affecting system performance; however, this vibration can also detect faults without stopping production, saving the company significant costs. In addition, the analysis of bearing vibration can also be used to detect problems in other parts of the rotating system. Therefore, bearing vibration analysis is of great significance for fault detection and monitoring of mechanical health.

In this paper, the problem of mechanical bearing fault detection is regarded as a time series analysis problem. The classical long short-term memory network analysis is used to capture the time series feature information in the bearing fault problem. Through a simple and effective attention module for feed-forward convolutional neural network, the attention map is inferred once through channel and spatial dimensions respectively, and then the attention map is multiplied with the input feature map for adaptive feature optimization. In order to evaluate the performance of the CBAM-LSTM model for bearing fault classification, this paper evaluates the method on the DataCastle bearing fault detection dataset.

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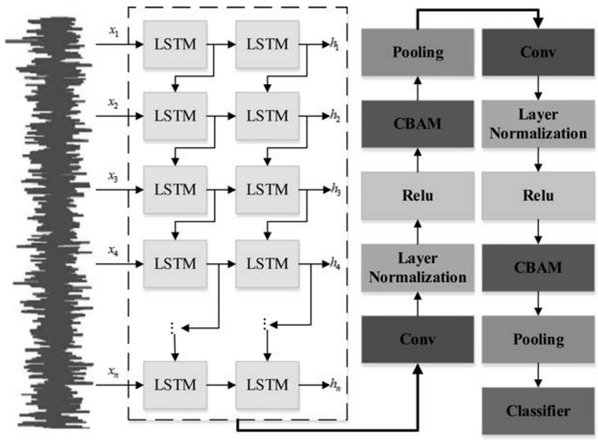

Figure 1 The structure of CBAM-LSTM

CBAM-LSTM MODEL

The CBAM-LSTM model is shown in Figure 1. CBAM-LSTM is a two-stage neural network model. The model first captures the sequence characteristics of bearing signals at different time points through two sets

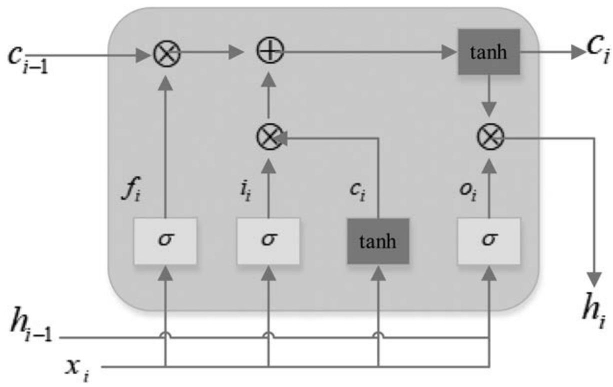

Figure 2 The network structure of LSTM

of LSTM models. The second stage uses a convolutional neural network, multilayer perceptron(MLP) and CBAM modules to learn channel and spatial two-dimensional feature information. The LSTM[1] model structure is shown in Figure 2.

f_i is the mathematical definition of the forgetting gate, such as formula 1. Firstly, the model determines which historical information is discarded through the forgetting gate.

$$f_i = \sigma(W_f[x_i, h_{i-1}] + b_f) \tag{1}$$

i_i is the input gate, and the output result of the ' forgotten ' selected by the forgotten gate is multiplied by C_{i-1}. The input gate is multiplied by $\widetilde{c_i}$ points, and then the above two parts are added to obtain the current moment C_i.

$$i_i = \sigma(W_i[x_i, h_{i-1}] + b_i) \tag{2}$$

$$o_i = \sigma(W_o[x_i, h_{i-1}] + b_o) \tag{3}$$

$$c_i = \tanh(W_c[x_i, h_{i-1}] + b_c) \tag{4}$$

$$C_i = f_i \odot C_{i-1} + i_i \odot \widetilde{c_i} \tag{5}$$

$$h_i = o_i \odot \tanh(C_i) \tag{6}$$

o_i is the output gate. The output gate first shunts C_i to pass the data stream to the next moment (i.e., C_{i+1} moment); on the other hand, the output gate controls the data stream through the tanh activation function and then performs the dot-multiplication operation with the output gate to get the hidden state h_i at the current moment.

The convolutional block attention module (CBAM) has channel attention module (CAM) and spatial attention module (SAM). CAM module focuses on the location information of the target area, and the SAM module performs feature extraction on the located area. The CBAM, CAM and SAM network structure is shown in Figures 3, 4, 5.

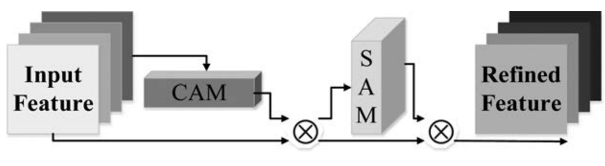

Figure 3 The network structure of CBAM

$$\text{CAM(x)=Sigmoid(MLP(AvgPool(x))} + \text{MLP(MaxPool(x)))} \tag{7}$$

As shown in formula 7. CAM changes the spatial dimension of the feature map x through the average pooling layer and the maximum pooling layer respectively. In this process, the channel dimension is kept unchanged. The output result is added after the MLP module, and finally the output result is obtained through the Sigmoid activation function.

In the SAM module, the CAM output feature results are again spliced by the two feature maps obtained by

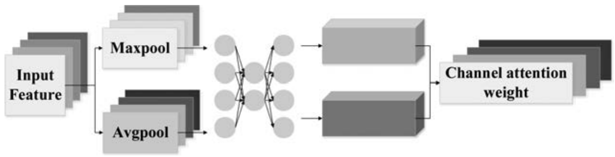

Figure 4 The network structure of CAM

average pooling and maximum pooling, and the number of channels is 1 by a convolution kernel of size n × n. Finally, the final SAM output is obtained by the Sigmoid activation function. The SAM mathematical definition is shown in Formula (8).

$$\text{SAM(x)=Sigmoid(f}_{n\times n}\text{([AvgPool(x));} \\ \text{MaxPool(x)]))} \tag{8}$$

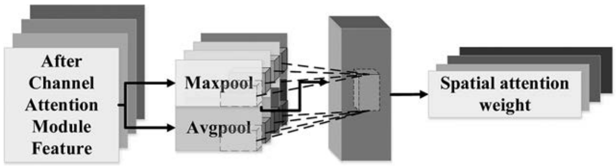

Figure 5 The network structure of SAM

Bearing data analysis

In practical engineering, bearings often operate under long-term operation, overload, corrosion, wear and other undesirable conditions, which can easily lead to faults in various parts of the bearing. At this time, the motor vibrates abnormally and the air gap magnetic field changes, resulting in harmonics in the stator current. According to the structure, the bearing can be divided into four parts : inner ring, outer ring, rolling element and cage, as shown in Figure 6. When each part is worn, corresponding faults will occur.

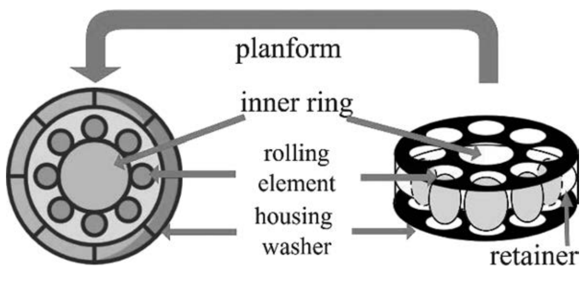

Figure 6 Bearing structure diagram

The fault of different parts of the bearing will produce vibration information of specific frequency. The mathematical definitions of inner ring fault f_{ir}, housing washer fault f_{hw}, rolling element fault f_{re}, and cage fault f_{bc} are shown in the formula.

$$f_{ir} = \frac{Nn}{120}\left(1 + \frac{d}{D}\cos\alpha\right) \tag{9}$$

$$f_{hw} = \frac{Nn}{120}\left(1 - \frac{d}{D}\cos\alpha\right) \tag{10}$$

$$f_{re} = \frac{n}{120}\left(1 - \frac{d}{D}\cos\alpha\right) \tag{11}$$

$$f_{bc} = \frac{Dn}{120d}\left[1 - \left(\frac{d}{D}\right)^2 \cos^2\alpha\right] \tag{12}$$

where D is the diameter of the cage, d is the diameter of the rolling body, α is the contact angle of the rolling body, and N is the number of balls. The bearing failure facts are shown in Figure 7.

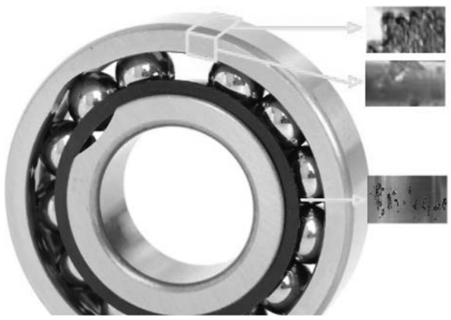

Figure 7 Examples of bearing failures

Bearing has 3 kinds of fault : housing washer fault, inner ring fault, ball fault, plus normal working condition. As shown in Table 1, combined with the three diameters of the bearing (Diameter 1, Diameter 2, Diameter 3), the working state of the bearing has 10 categories : In the experiment, the data set is divided into training and validation set (792 data), test set (528 data), and the training set and validation set are used to train and cross-validate multiple parameter combinations to verify the selection of better hyperparameters and finally test the model performance results on the test set.

Table 1 **Bearing fault data categories**

	Diameter 1	Diameter 2	Diameter 3
Housing Washer Fault	1	4	7
Inner Ring Fault	2	5	8
Rolling Element Fault	3	6	9
Normal bearings	0		

EXPERIMENT AND ANALYSIS

The data set used in this article comes from DataCastle sampling of time series data from bearing rotation vibrations, which are vibration signals continuously sampled in time series from 1 to 6 000. There are 10 categories of signals. Details of data categories are shown in Figure 8.

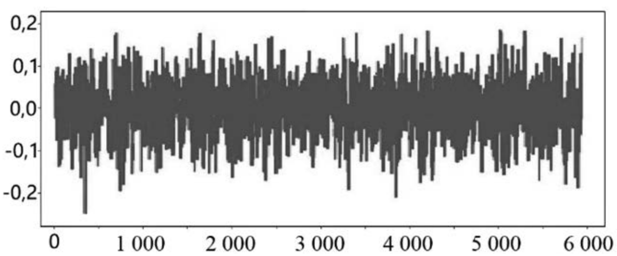

Figure 8 Examples of bearing failures

The experimental operating system is Ubuntu20,04, GPU model is NVIDIA GeForce GTX 3060ti, and the memory size is 12GB. The network framework uses pytorch1,8, and the programming language environment is python 3,6 and Cuda 11,1. The network parameters are set as follows: using Adam optimizer, the initial learning rate is 0,001. In this paper, Accuracy (ACC) is used as the evaluation index of fault bearing detection. The epoch parameter is set to 50. The mathematical definition of ACC is shown in the formula .

$$Acc = \frac{TP + TN}{TP + FP + FN + TN} \tag{13}$$

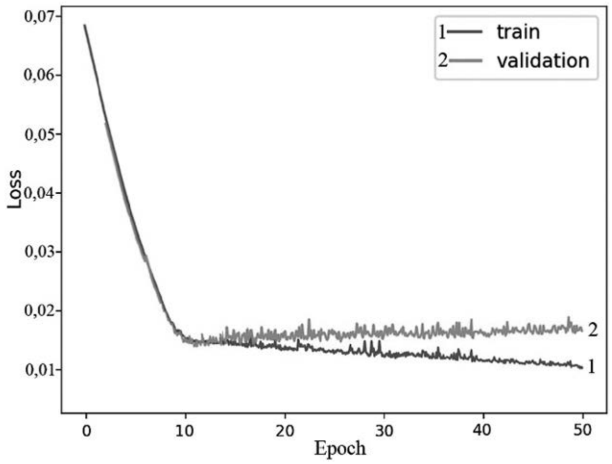

Figure 9 The loss curve of CBAM-LSTM model

As shown in Figure 9, the CBAM-LSTM model has reached the lowest loss value of the validation set at the 10th epoch. In this paper, the 30th round parameter is taken as the test set model parameter to verify the results of 10 categories (as shown in Figure 10).

In order to verify the validity of the model, this paper compares four classic machine learning baseline models(Random Forest[2], SVM[3], KNN[4], MLP[5], and the comparison results are shown in Figure 11. Compare the experimental results, the average accuracy of CBAM-LSTM model on 9 fault categories and 1 standard bearing reaches 99,137 %.

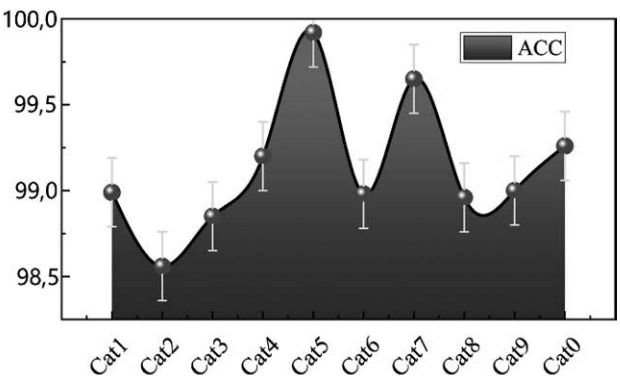

Figure 10 Comparative experiments of 10 categories of bearings on DataCastle dataset

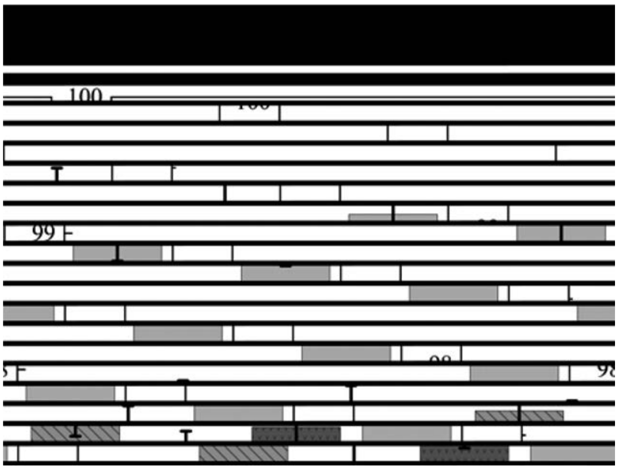

Figure 11 Comparative experiment of different models

CONCLUSION

This paper presents a fault bearing detection method based on CBAM-LSTM network model. The paper discusses the model in 9 kinds of bearing fault classification and a standard bearing signal. In this paper, four classical machine learning models are compared and the performance of CSTM-LSTM in bearing fault detection is compared and analyzed through experiments. Experiments show that the model has better resolution for some bearing fault problems and can effectively reduce the factory loss caused by bearing faults.

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