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# Research on Rolling Bearing Fault Identification Method Based on LSTM Neural Network

Pan Luo<sup>2</sup>, Yumei Hu<sup>1</sup>

1. State Key Laboratory of Mechanical Transmission, Chongqing University, Chongqing, 400024;

2. School of Automotive Engineering, Chongqing University, Chongqing, 400024

E-mail: 1120593594@qq.com

**Abstract:** In order to simplify the fault detection process, improve the efficiency of fault detection and recognition accuracy, a rolling bearing fault recognition based on LSTM neural network is proposed. In this model, there is no need to perform any preprocessing on the original data. As long as the neural network model training is completed, the original signal can be detected and identified automatically by the model. In order to verify the performance of the model, the test results of the same fault data set are compared with the fault recognition model based on traditional machine learning. The results show that the fault recognition model based on LSTM neural network has obvious superior performance and higher recognition reliability. Its recognition accuracy rate reaches 98.00%, and the recognition accuracy of the fault recognition model based on traditional machine learning is only 94.20%.

**Key words:** fault recognition; LSTM recurrent neural network; feature learning; machine learning; vibration analysis

## 1. Introduction

Rolling bearings are the most widely used components in gearboxes, and their operating conditions directly affect the overall performance of the gearbox. Therefore, accurate and efficient detection of bearing faults has important practical significance. In recent decades, researchers have proposed many machine-based fault detection models. Among them, Fengqi Wu proposed a support vector machine trained by a small amount of raw data, and then directly diagnosed the fault [1], which verified the feasibility of the machine learning model in fault recognition. Since the recognition accuracy of machine learning fault recognition model depends heavily on input features, the recognition accuracy of this method is not high. In order to improve the accuracy of machine learning fault recognition model, many feature extraction methods have been proposed by researchers, such as Zaeri R extracted mathematical and statistical features of wavelet coefficients from raw data as input data of neural network model [2], Kateris D directly extracted the mathematical statistics of the original data as the input data of the neural network model [3]. Jianguo Wang proposed the Empirical Mode Decomposition (EMD) of the original data, and the energy of each EMD component as the input data of support vector machine classifier[4]. The above feature extraction methods can improve the accuracy of the fault recognition model through



machine learning. However, it is necessary to carefully design the feature engineering, which requires a lot of time, labor costs, and requires the technician to have signal processing and engineering practical experience.

In recent years, deep learning technology has been able to implement end-to-end learning for raw data due to its powerful feature extraction ability, which has attracted widespread attention[5]. Because of the characteristics of in-depth learning, some researchers have applied it to mechanical fault recognition, such as L Jiang and Z Ge proposed a fault recognition model of self-coding machine. The model can automatically extract data features and improve the efficiency of fault recognition, but the accuracy of the model still has much room to further improve [6]. Xiaoxi Ding and Qingbo He proposed a fault detection model based on convolution neural network. Although the model has good recognition accuracy, it needs to construct a complex data preprocessing process of wavelet scale energy map first.

In order to overcome the defects of the model in fault recognition, improve the efficiency and accuracy of fault recognition, a rolling bearing fault recognition model based on LSTM neural network is presented in this paper. The model first constructs a training input sequence by intercepting the sample data of length 1024 through a one-dimensional time window which window length and step size are both of 32, and then training the model. After training, the input data sequence is constructed by intercepting the same length of signal to be detected in the same window, and finally the model performs fault identification and classification on the input sequence. Finally, four commonly used machine learning models for fault recognition are selected, including SVC, KNC, DTC and ANN. The differences of recognition accuracy and speed between the four models and the LSTM neural network model adopted in this paper are compared.

## 2 Machine Learning Model and LSTM Model

### 2.1 Feature Engineering

Feature engineering is an engineering activity that extracts data features from raw data by certain methods for model or algorithm use. Vibration signals depend on the operation state of machinery and contain abundant information about the operation state of machinery, so they are often used for fault detection. Currently what are used for fault recognition are time-based mathematical statistical features such as: Kurtosis, Crestor Factor, RMS, etc. The feature calculation formulas used in this paper are as follows [3]:

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (1)$$

$$Kurtosis\ Indicator = \frac{\sum_{i=1}^N (x_i - \mu_x)^4}{N \sigma_x^4} \quad (2)$$

$$Crest\ Indicator = \frac{\max |x_i|}{\sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}} \quad (3)$$

$$Clearance\ Indicator = \frac{\max |x_i|}{\left( \frac{1}{N} \sum_{i=1}^N \sqrt{|x_i|} \right)^2} \quad (4)$$

$$\text{Shape Indicator} = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}}{\frac{1}{N} \sum_{i=1}^N |x_i|} \quad (5)$$

$$\text{Impulse Indicator} = \frac{\max |x_i|}{\sqrt{\frac{1}{N} \sum_{i=1}^N |x_i|}} \quad (6)$$

In order to improve the performance of machine learning fault recognition model, it is usually necessary to design feature engineering. Due to the difficulty in interpreting the data features extracted from feature engineering, the design difficulty of feature engineering is increased to some extent.

### 2.2 Machine learning

At present, machine learning technology is a common method in mechanical fault recognition. Usually we think that the occurrence of abnormal data indicates that the machinery has failed during the operation. In the process of fault detection, we need to extract data features from the original data obtained in the process of mechanical operation by feature engineering, and then use machine learning models such as support vector machine [1], clustering analysis [8], and neural network [2] to identify faults.

The main difference between machine learning fault recognition model and traditional methods is that the input data can be quickly detected and identified after the model training is completed by the feature extracted from the feature engineering mentioned in the previous section. Compared with traditional fault recognition methods, machine learning fault recognition model has greatly improved the recognition efficiency. However, the data preprocessing process of Feature Engineering limits the performance of machine learning model in fault recognition.

### 2.3 Feature learning

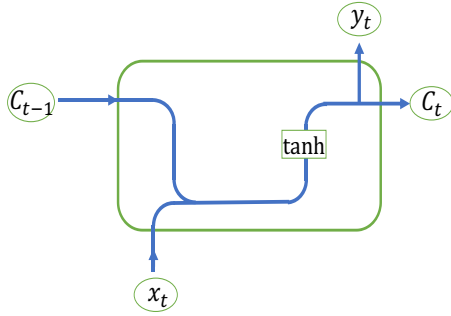
Feature learning refers to the collection of related technologies such as feature conversion from raw data. It is significantly different from feature engineering. Feature engineering is to extract data features through a series of formulas, and then select features through the principles of divergence and correlation, and finally select efficient features for recognition and classification. Feature learning is to automatically learn the relevant features through a series of transformations of the original data by the model itself, and finally classify the data. In feature learning, the model will iterate over and over again to correct empirical errors to extract effective data features. Therefore, the features extracted from feature learning model can better express data. That means we can get the optimal features for recognition tasks.

### 2.4 LSTM model

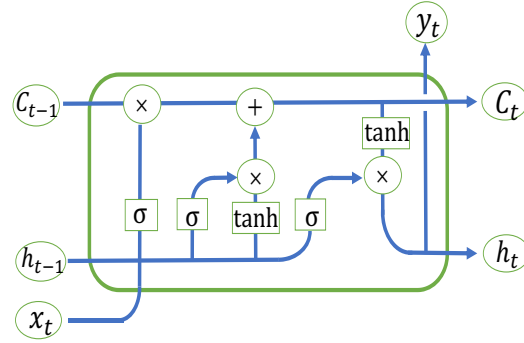
In the traditional neural network model, since the nodes between the layers are independent of each other, the connection between the input data cannot be effectively established. However, sequence data is generally considered to be related to each other, which makes traditional neural networks unable to process sequence data efficiently. In the Recurrent Neural Network (RNN), the output of the current time of the neuron is affected by the output of the neurons at different times before, that is, the model stores and uses the input of the neuron at different times. Thus it can establish the relationship between the input data at different times. Its network neural unit structure is shown in Figure 1.

The RNN model contains input units, the input data is marked as  $X = \{x_1, x_2, \dots, x_t, \dots, x_{32}\}$  ( $x_t$  representing the input of the time  $t$  neuron), and the output unit is marked as  $Y = \{y_1, y_2, \dots, y_t, \dots, y_{32}\}$  ( $y_t$  representing the output of the time  $t$  neuron), and the update-output unit is marked as  $C = \{c_1, c_2, \dots, c_t, \dots, c_{32}\}$  ( $c_t$  representing the update status of the time  $t$  neuron). There are two information flows in RNN. One is from the input unit to the hidden unit, the other is from the hidden unit

to the output unit. There is only one simple activation function in the RNN neuron unit. If the information flow is too long, the RNN will have the disadvantageous effect of gradient disappearance or gradient explosion when it is trained by Back propagation Through Time (BPTT)[9]. To overcome the shortcoming of RNN neural network, LSTM neural network is proposed by researchers. LSTM neural network solves this problem by using four threshold structures instead of simple state update units widely used in RNN[10]. Due to the existence of these four threshold structures, the LSTM neural network's memory storage capacity is greatly improved. The LSTM neuron structure is shown in Figure 2, the  $H = \{h_1, h_2, \dots, h_n\}$  ( $h_i$  representing the hidden output of T neurons).



**Figure 1** RNN unit structure



**Figure.2** LSTM Cell Structure

The LSTM formula is as follows::

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (7)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (8)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (9)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (10)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (11)$$

$$h_t = o_t \cdot \tanh(C_t) \quad (12)$$

$f$ ,  $i$ ,  $o$  and  $C$  respectively represent forgotten gate, input door, output door and update door.

$\sigma_x$  and  $\tanh_x$  are activation functions, which are defined as follows:

$$\sigma_x = \frac{1}{1 + e^{-x}} \quad (13)$$

$$\tanh_x = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (14)$$

To classify the extracted features, the final output of the LSTM network is used as input to the Softmax layer. The Softmax layer output formula is as follows

$$y_t = W_y \cdot h_t + b_y \quad (15)$$

$$pred_i = \frac{e^{w_i y_i + b_i}}{1 + \sum_{i=1}^N e^{w_i y_i + b_i}} \quad (16)$$

In the formula:  $w_i$  is the  $i$ -th weight matrix.

### 3. Experiment and result comparison

#### 3.1 Data set description

The data in this paper are from the gearbox fault data set opened by the Case Western Reserve University Bearing Data Center. The test data were sampled at 12 kHz at three different locations under four different load conditions (0 hp, 1 hp, 2 hp, 3 hp). This paper selects the drive side measurement data with load of 3hp, which contains 10 sets of data (9 sets of fault data and 1 set of normal data). The types of faults are divided into three categories according to bearing diameters: 0.07 inches, 0.14 inches, and 0.21 inches. Each category is further classified into three types of sub-faults: ball failure, inner ring failure, and outer ring failure. Each set of data contains 100 samples (divided into one sample every 1024 points, each sample length is 1024), in which training data and test data each account for 50%. In order to facilitate training, one-hot coding of fault types is carried out, as shown in Table 1.

For feature engineering, six features are extracted from each sample by formulas (1)-(6) to construct a one-dimensional input feature vector; for feature learning, a one-dimensional time window with a window length and a step size of 32 is used to perform 32 intercepts for each sample to construct LSTM neural network fault identification model input data.

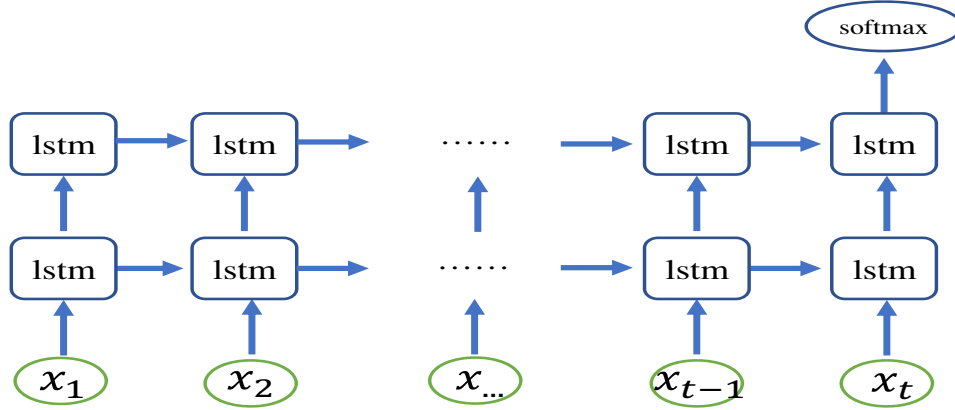
In this paper, four different machine learning models are used to identify faults: Artificial Neural Network (ANN), Decision Tree Classifier (DTC), Support Vector Machine Classifier (SVC), and K Nearest Neighbor Classifier (KNC). Since the performance of the above model is affected by its hyperplane parameters, in order to obtain reliable test results, the hyperplane parameters of each model are optimized by the grid search method [11], and the model with the best performance is selected as the final test model.

**Table 1** raw data table

fault size	fault type	markup symbol	fault number
0	normal	normal	0
0.07	ball failure	b-0.07	1
0.07	inner ring failure	ir-0.07	2
0.07	outer ring failure	or-0.07	3
0.14	ball failure	b-0.14	4
0.14	inner ring failure	ir-0.14	5
0.14	outer ring failure	or-0.14	6
0.21	ball failure	b-0.21	7
0.21	inner ring failure	ir-0.21	8
0.21	outer ring failure	or-0.21	9

The LSTM neural network model used in the feature learning method has four layers, which are divided into input layer, hidden layer (two-layer LSTM structure, each layer length is 32), and output layer (Softmax layer). The model structure is shown in Figure 3. The number of each LSTM neural network unit is set to 128, the training set (Batch size) is set to 50, and the Epochs is set to 150. In order to avoid over-fitting of the neural network, Dropout operation is performed in each hidden layer, and the Dropout rate is set to 0.5[12]. Before the training data is input into the network, the random shuffling operation is first performed, but the test data is not operated.

The LSTM neural network fault detection model proposed in this paper is based on the TensorFlow\_gpu-1.7 version. The running platform is a desktop computer (Win7 64-bits system, 3.4GHZ CPU, GTX-950 GPU, 12G memory).



**Fig.3** Model Structure

### 3.2 Comparison of results

#### 3.2.1 Evaluation indicators

In order to measure the performance difference between the fault recognition model proposed in this paper and the machine learning fault recognition model, four performance evaluation indicators are selected in this paper: Accuracy, Precision, Recall and F1\_score. The calculation formula are as follows:

$$Accuracy = \frac{|TP| + |TN|}{|TP| + |FP| + |TN| + |FN|} \quad (17)$$

$$Precision = \frac{|TP|}{|TP| + |FP|} \quad (18)$$

$$Recall = \frac{|TP|}{|TP| + |FN|} \quad (19)$$

$$F_1\_score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (20)$$

In the formula: | TP | denotes the total number of correctly judged faults; | TN | denotes the total number of correctly judged normal states; | FP | denotes the total number of incorrectly judged faults; | FN | denotes the total number of incorrectly judged normal states

When the model is used to detect fault, it is difficult to avoid incorrect judgments in the recognition results. Therefore, we require a reliable fault recognition model with good recognition accuracy. When the fault recognition model need identify a large number of data, the number of misjudgments in the recognition results may increase. To avoid the occurrence of this phenomenon, “Precision” as a evaluation index is introduced. In addition, if only real faults occur and some real faults are neglected in the recognition results, the “Precision” will be improved, but the recall rate will be reduced, and F1\_score will comprehensively measure the precision and recall rate. Therefore, the above four indicators should be optimized simultaneously for the fault identification model to ensure that the model can identify faults while reducing the probability of false diagnosis and real fault omission.

#### 3.2.2 Comparing the results of different models

The initial performance table and optimization performance table of the four machine learning fault detection models selected in this paper are shown in Table 2 and Table 3. A comparison of Table 2 and

Table 3 shows that the performance of the optimized machine learning model has been improved to varying degrees. The SVC model has the highest performance improvement, and the four performance indicators after optimization are higher than those of other models, and the recognition accuracy is 94.20% from the initial 78.20%. Figure 5 shows that the optimized SVC model greatly improves the accuracy of identification of health conditions and fault conditions, and can better distinguish between health status and fault status. However, comparing Fig. 4 and Fig. 5, it can be found that the three faults at 0.14 inches are still difficult to identify, and the optimized SVC model has no obvious improvement effect. This may be because the features extracted based on feature engineering at this size cannot contain enough effective information. Therefore, the different faults under this size are judged by the SVC fault identification model, and the accuracy is low, which affects the overall performance index of the model. .

For the LSTM fault identification model, in order to ensure the performance of the LSTM neural network fault identification model during the test, a checkpoint strategy is adopted in the training process. That is, when the accuracy of the LSTM neural network fault recognition model reaches the current highest value in the test data set, the model is saved once, and finally the result with high test accuracy is selected as the final test result. Its performance comparison table and confusion matrix are as follows. Table 4 shows that the LSTM neural network fault identification model has better performance than the optimized SVC fault identification model. Its performance evaluation indicators are higher than the SVC fault identification model, in which: the recognition accuracy rate is up to 98.00%. Figure 5 and Figure 6 show that compared with the SVC fault identification model, the LSTM neural network can distinguish fault signals and normal signals more accurately, and there is basically no misjudgment. Although the accuracy of individual fault type recognition has not reached the average value of model identification accuracy, its lowest accuracy still reaches 90%, which is still much higher than the minimum accuracy of the SVC model. At the same time, the recognition accuracy of the three types of faults that are prone to confusion in the SVC model is significantly improved in the LSTM neural network fault identification model. In summary, the LSTM neural network fault identification model proposed in this paper has better identification reliability. We can visualize the working state of LSTM model in the process of feature extraction. Figure 7 is a scatter plot of feature extraction of LSTM model at different times.

**Table 2** Initial Performance Table

score	SVC	KNC	DTC	ANN
Accuracy	78.60%	87.60%	93.40%	89.00%
Precision	79.80%	88.13%	93.82%	89.20%
Recall	78.60%	87.60%	93.40%	89.00%
F1_score	76.02%	87.46%	93.54%	88.80%

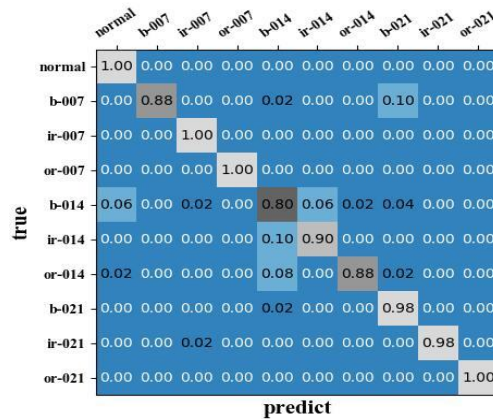
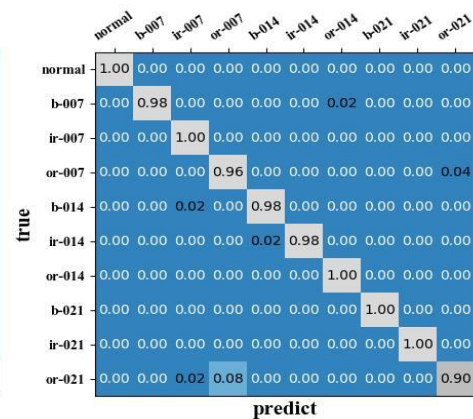
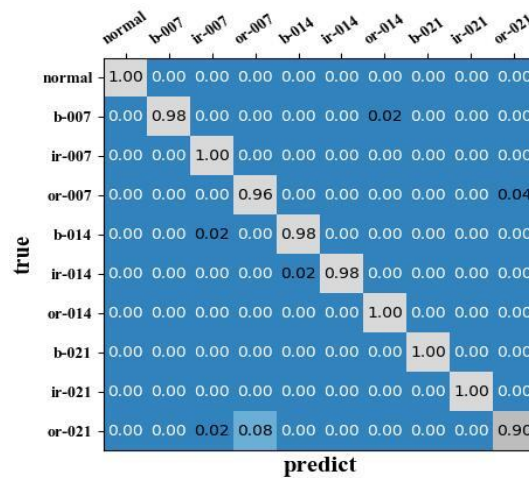
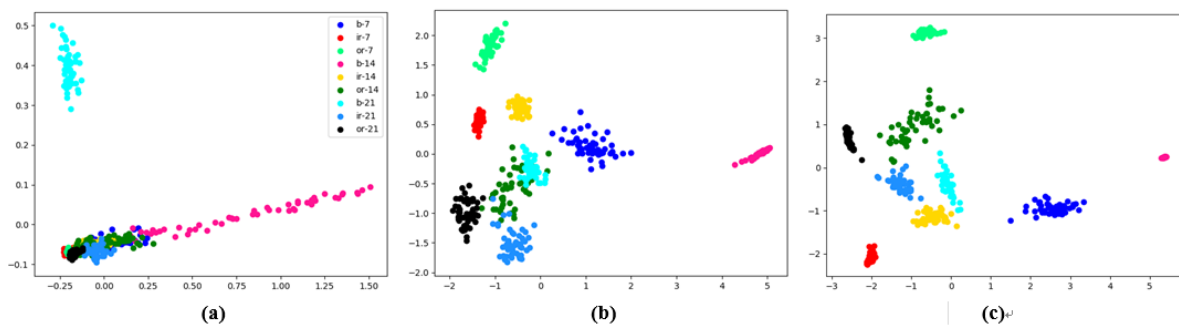
**Table 3** Optimization Performance Table

score	SVC	KNC	DTC	ANN
Accuracy	94.20%	90.00%	93.40%	92.60%
Precision	94.56%	90.23%	93.82%	92.70%
Recall	94.20%	90.00%	93.40%	92.60%
F1_score	94.31%	90.01%	93.54%	92.56%



**Table 4** Final Performance Table

score	Accuracy	Precision	Recall	F1_score
SVC	94.20%	94.56%	94.20%	94.31%
LSTM	98.00%	98.02%	98.00%	97.99%

**Fig.4** SVC Initial Confusion Matrix**Fig.5** SVC Optimization Confusion Matrix**Fig.6** LSTM Confusion Matrix

**Fig.7** Scatter plots at different times of the extracted features for data set E by LSTM((a) is the initial time; (b) is the middle time; (c) is the end time )

From figure 7, we can clearly see the working process of LSTM model in extracting features. On the right side of Figure 7, we can see that all kinds of fault types have clear boundaries and no overlapping categories. This intuitively shows that LSTM model has a very strong feature extraction capability. So LSTM has excellent fault recognition ability.

#### 4. Conclusion

1) In this paper, a rolling bearing fault recognition model based on LSTM neural network is proposed. When the fault detection and recognition is carried out, the original data need not be pre-processed, and it has high fault recognition efficiency and speed.

2) The fault recognition model based on LSTM neural network can fully exploit the potential information of the original data, better express the original data, and has excellent recognition reliability.

3) Compared with the experimental results of machine learning model in gear box fault data set, the results show that the proposed LSTM-based neural network fault recognition model has better performance and provide a new method and idea for gear box fault recognition.

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