Viser Technology Pte. Ltd.
Mechanical Engineering Science
DOI: 10.33142/mes.v4i2.9085

Research Article Open Access

CNN-LSTM based on attention mechanism for brake pad remaining life prediction

Shuo WANG, Zhenliang YU*, Guangchen XU, Sisi CHEN

Yingkou Institute of Technology, School of Mechanical and Power Engineering Yingkou, China

***Corresponding Author:** Zhenliang YU, email address:yuzhenliang_neu@163.com*

Abstract:
In order to predict the remaining service life of brake pads accurately and efficiently, and to achieve intelligent warning, this paper proposes a CNN-LSTM brake pad remaining life prediction model based on an attention mechanism. The model constructs a non-linear relationship between brake pad features such as brake temperature, brake oil pressure and brake speed and brake pad wear data through convolutional neural network (CNN) and long and short term memory network (LSTM), as well as capturing the time dependence that exists in the brake pad wear sequence. The attention mechanism is also introduced to assign different weight values to the features output from multiple historical moments, highlighting the features with high saliency and avoiding the influence of invalid features, so as to improve the prediction effect of the remaining brake pad life. The results show that the proposed CNN-LSTM-Attention model can effectively predict the remaining life of brake pads, with the mean absolute error MAE value of 0.0048, root mean square error RMSE value of 0.0059 and coefficient of determination R2 value of 0.9636; and compared with the BP model, CNN model, LSTM model and CNN-LSTM model, the coefficient of determination R2 values are closest to 1, with an improvement of 8.26%, 5.25%, 3.99% and 1.85% respectively, enabling more effective monitoring and intelligent warning of the remaining brake pad life.
***Keywords:** attention mechanism; CNN-LSTM; brake pads; life prediction*

1 Introduction

As people's living standards improve, the number of cars owned increases, and so does the probability of traffic accidents. As one of the important protection devices for safe driving, car brakes are of great concern, and their performance directly affects the personal safety of people driving cars. During the braking process, the brake pads and the brake discs produce relative motion, which instantly generates great temperature and friction, and the surface of the brake pads is prone to wear due to chemical reactions under high temperature and pressure. Therefore, it is necessary to make accurate life prediction and health management of the brake pads, so that the management system can make intelligent alarm according to the prediction result and remind the driver to replace the brake pads in time, thus avoiding major traffic accidents.

At the same time people's requirements for the reliability and safety of cars are getting higher and higher, and new requirements for the failure mechanisms, and diagnostic techniques of vehicle braking systems have been put forward, and the research literature on vehicle braking system fault diagnosis is becoming increasingly rich. Deng Fengman et al. based on fuzzy theory for hydraulic brake system fault diagnosis, the accuracy of the constructed ARX-RBQ diagnosis model is 92%, indicating that the use of the model can basically complete the fault diagnosis of hydraulic brake system [1] . However, the research on the remaining life prediction and intelligent warning of brake pads in vehicle braking system is very limited, and the early prediction is mainly for the design life of brake pads using theoretical or experimental methods to verify. Hao Mingshu et al. used the Manson-Coffin equation to predict the thermal fatigue life of disc brakes by studying the temperature and stress fields of disc brakes and deriving the average equivalent force at the hazardous parts of the disc [2].

The mid-to-late stage prediction mainly uses machine learning methods to extract and train features from the collected raw data, simulate the whole process of system degradation, and compare the current working state with historical data to complete the prediction of remaining life. The most commonly used machine learning methods mainly include BP neural networks [3], artificial neural networks (ANN) [4], Support vector machines (SVM) [5] etc. However, machine learning methods do not dig deep into the hidden information of

Received on October 9, 2022; Accepted on December 13, 2022

the data and do not consider the intrinsic correlation of the time series, which still needs to be improved.

In recent years, deep learning theory has emerged in the field of residual life prediction, which is able to extract deep features from complex data and combine them with time series information to predict residual life compared to traditional mechanical learning techniques [6]. The most commonly used deep learning algorithms include recurrent learning. The most commonly used deep learning algorithms include recurrent neural networks (RNN), long and short-term memory networks (LSTM) and convolutional neural networks (CNN).

Recurrent neural networks (RNNs) can handle time series data and can remember the intrinsic connections between systems in time steps, but are prone to gradient explosion or gradient disappearance and can only handle short-term memory problems [7]. Long Short Term Memory Networks (LSTM) can solve these problems by not only handling long term memory, but also by linking past and future time series [8]. Recently, work on the prediction of the remaining life of brake pads based on LSTM has been gradually carried out by Xu Meng The results show that the VMD-Bi LSTM model can meet the requirements of brake pad life prediction[9]. However, the prediction accuracy and precision of the LSTM network is not high for the time series with stronger non-linearity and more prominent non-smoothness [10].

In order to obtain better prediction results in the field of time-series data prediction, Riemer et al. proposed a neural network based on an attention mechanism for multi-source time-series data [11]. The input attention mechanism is introduced in the encoder stage to filter more relevant features for prediction, and the temporal attention is introduced in the decoder stage to extract the long-term time dependence of time series, thus avoiding the influence of invalid features and improving the model accuracy [12].

Convolutional neural networks (CNNs) are also widely used in various models for lifetime prediction because their convolution and pooling operations can improve the ability to mine potential features of complex data in prediction models compared to long and short-term memory networks (LSTMs) [13]. However, CNN networks are only able to extract the most important features of the data. However, CNN networks can only extract spatial features of brake pad wear and avoid temporal information, which leads to incomplete extraction of brake pad wear prediction features and reduced accuracy and efficiency of prediction[14]. Therefore, it has become an inevitable trend to combine CNN models with LSTM models.

The wear of automotive brake pads is a process of gradual degradation over time, which is by nature an asymptotic, non-linear and non-stationary time series with a severe dependence on time. Therefore, based on machine vision, feature extraction, deep learning, attention mechanism and other techniques, this paper proposes a CNN-LSTM brake pad remaining life dynamic evaluation method based on attention mechanism improvement, using CNN model to mention mining potential deep features in space and capturing time series information in time through LSTM model, so that the temporal features and spatial features of the data can be fully utilized. thereby improving the accuracy of brake pad wear prediction. Finally, an attention mechanism is introduced to deal with the difference in importance of the CNN-LSTM output features to enhance the influence of important time-series features in the model, avoid memory loss and gradient dispersion caused by too long a step, and improve the model prediction effect. The research of this method will propose a new theory and method for the prediction of the remaining life of brake pad wear, laying a theoretical foundation and scientific basis for improving the development of China's automobile manufacturing industry and automobile maintenance industry.

2 Life estimation options for automotive brake pads

The braking principle of a car is to use the friction between the brake pads and the brake disc to convert the kinetic energy of the car moving forward into the heat energy after friction, thus stopping the car. As shown in Figure 1, when the car brakes, the caliper piston pushes the brake pad under the action of hydraulic fluid, and the brake pad and the brake disc come into contact with each other to produce sliding friction, which eventually holds the brake disc to stop the car. Most of the brake pads are made of polymer-based composite materials, so this paper uses the quantitative calculation of wear of composite materials as a reference to estimate the wear of brake pads and obtains the following equation:

$$\Delta H = \alpha P^a V^b t^c \tag{1}$$

where ΔH is the amount of wear generated during the braking process of the car brake pad, P is the oil pressure of the hydraulic oil pushing the piston, V is the relative velocity between the brake pad and the brake pad, t is the friction time during the braking process, and α is the compensation coefficient of brake pad wear, a, b and c are the indices of brake oil pressure, braking speed and braking time respectively.

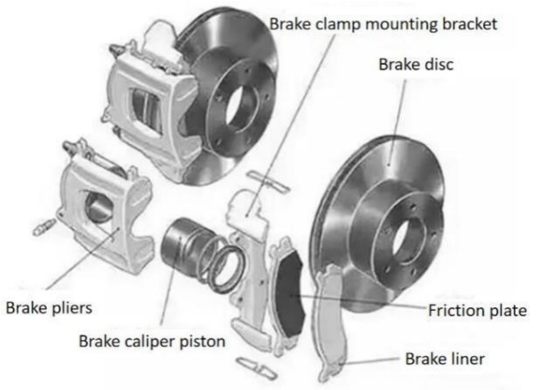


Figure 1 Structure of a car brake

During the braking process, the brake pads and brake discs generate a lot of heat in contact with each other, causing a chemical reaction on their surface resulting in wear. If we consider the frictional heat generated by the chemical reaction, the frictional heat coefficient is θ, theΔH_V In order to consider the amount of wear on the brake pads of the car after the chemical reaction, we are able to derive the following formula:

$$\Delta H_V = \Delta H * \theta = \alpha\theta P^a V^b t^c \tag{2}$$

Four parametric correction equation according to the Arrhenius formula:

$$\theta = \beta(T/T_0)^n e^{-E/RT} \tag{3}$$

where β, n is a constant; E is the activation energy generated by friction between the brake pad and the brake disc; R is the molar gas constant; T is the real-time temperature of the brake pad; T_0 is the initial temperature of the brake pad; and

It is therefore possible to derive an equation for the amount of brake pad wear after taking into account the chemical reaction:

$$\Delta H_V = \Delta H * \theta = \alpha\theta P^a V^b t^c = \alpha\beta P^a V^b t^c (T/T_0)^n e^{-E/RT} \tag{4}$$

The above equation shows that the real-time temperature of the brake pads, the oil pressure of the hydraulic fluid pushing the piston and the relative speed between the brake pads and the brake pads are all decisive factors in the wear of the car's brake pads.

3 Construction of a method for predicting the remaining life of brake pads

In order to improve the accuracy and precision of the brake pad remaining life prediction model, this paper proposes a life prediction model based on the improved CNN-LSTM with attention mechanism, which outputs the wear value of the brake pad by detecting the braking speed, braking pressure and braking temperature, so as to calculate the remaining thickness of the brake pad according to the initial amount of the brake pad, and will generate a failure alarm prompt when the remaining thickness exceeds the wear threshold, with The improvements are:

(1) The extracted braking speed, brake oil pressure and brake temperature features are batch normalised to improve the generalisation capability of the model, avoid over-fitting and improve the convergence speed of the model.

(2) The unique structure of the CNN model with local connectivity and weight sharing allows the complexity of the network to be reduced, and the spatial continuity of the sample features is maintained after convolution and pooling operations.

(3) The Long Short Term Memory Network (LSTM) is a further optimisation of the traditional RNN network, capable of handling longer time series data while avoiding gradient disappearance or gradient explosion phenomena.

(4) The introduction of the Attention mechanism can handle the importance variability of the CNN-LSTM output features, complete with the assignment of different weight values to avoid the influence of invalid features and improve the model accuracy. Its CNN-LSTM-Attention brake pad remaining life prediction model is shown in Figure 2.

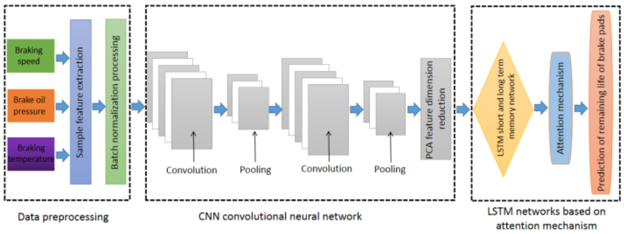


Figure 2 CNN-LSTM-Attention remaining life prediction model

3.1 Construction of the sample data set

Braking speed refers to the relative speed of sliding friction between brake pads and brake pads. The relative speed is measured by the speed sensor. In this paper, according to the national road safety regulations, the vehicle speed is controlled between 40km/h and 120km/h, so the extracted braking speed range is 354r/min to 1061r/min. Brake oil pressure refers to the hydraulic oil pressure that the piston pushes the brake pad to lock the brake disc. The pressure of the hydraulic oil to push the piston is extracted through the hydraulic pressure sensor. In this paper, according to the relevant requirements of the automobile brake performance, the brake pressure is controlled at 0.8Mpa to 1.6Mpa; Braking temperature refers to the instantaneous temperature generated by the friction between brake pads and brake discs. Real-time temperature of brake pads is extracted by temperature sensor, and the extracted temperature ranges from 47.4℃ to 84.7℃. The braking parameters are shown in Table 1.

Table 1 Selection range of braking parameters

Braking parameters	Sensors	Parameter range
Braking speed	Speed Sensors	354r/min to 1061r/min
Brake oil pressure	Oil pressure Sensors	0.8Mpa to 1.6Mpa
Braking temperature	Temperature Sensors	47.4° C to 84.7° C

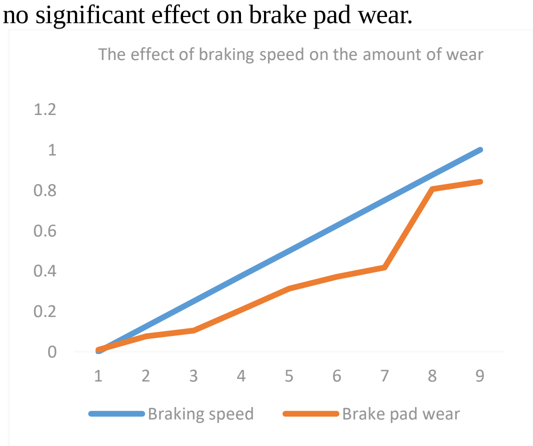
In this paper, the raw data of the above three braking parameters and the wear of the brake pads after braking are extracted separately, but the wear of the brake pads after a single braking is small and difficult to measure, so the braking feature extraction experiments are conducted every Δt time. In this experiment, the number of braking cycles in Δt time was set to 300, and the braking parameters were kept constant, so each feature extraction experiment was able to obtain three time-domain features: braking speed, braking oil pressure and braking temperature. A total of 50 feature extraction experiments were carried out, so a 50 x 3 feature sample matrix can be derived, which is the input to the brake pad residual life prediction model; at the same time, the thickness of the brake pad before and after braking in Δt time is measured, and the difference is divided by the number of braking times to determine the amount of brake pad wear after each braking, so a 50 x 1 target sample matrix can be derived, which is the output of the brake pad residual life prediction model. This matrix is the output of the brake pad residual life prediction model.

In order to improve the generalization ability of the prediction model and to find out the degree of influence of the three braking parameters on brake pad wear, the 50 x 3 feature sample matrix and the brake pad wear values obtained above were normalized by the normalization process formula:

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (5)$$

Where X is the sample of each feature, and X_{min} is the minimum value of the sample feature, and X_{max} is the maximum value of the sample feature.

Figure 3 shows the effect of each braking parameter on brake pad wear after normalisation. From Figure 3, it can be seen that, according to the experiment conducted in accordance with the above requirements, with the increase of braking speed, braking pressure and braking temperature, the wear of automobile brake pads all course upwards; however, braking speed and braking temperature have a greater effect on brake pad wear, while braking pressure has no significant effect on brake pad wear.



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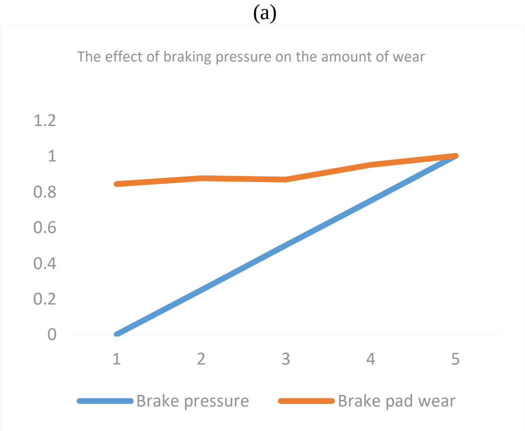

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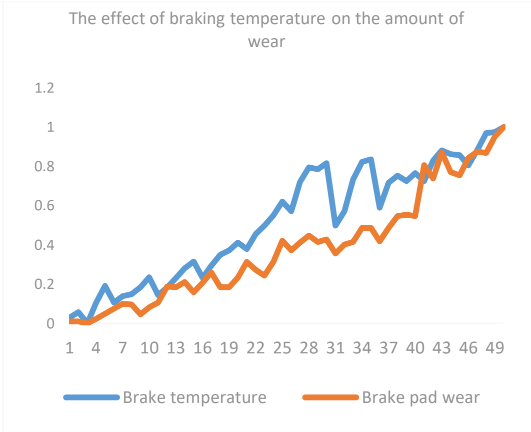


(C)

Figure 3 Effect of braking parameters on brake pad wear.(a) Effect of braking speed on the amount of wear.(b) Effect of braking pressure on the amount of wear.(c) Effect of braking temperature on the amount of wear

3.2 Prediction principles of CNN-LSTM-Attention models

3.2.1 Convolutional Neural Networks (CNN)

The CNN convolutional neural network proposed by LeCun Y et al. is a typical representative of deep learning and is widely used for processing spatial features [15]. In this paper, CNN convolutional neural networks are used to extract the local correlation features between the sample data of the braking system and the wear and tear values in the target samples, and remove the unstable information and noise while maintaining the spatial continuity of the samples, resulting in a high-dimensional feature matrix as the input to the LSTM network, which is based on the following principles:

(1) Convolution operations are performed on the batch normalised sample matrix by using a convolution kernel of suitable dimensionality to abstractly represent the brake pad wear features in space. Let the jth feature data output from layer i-1 be X_{i-1}^{j} , and in order to improve the prediction accuracy of the model, this paper chooses the Relu function as the activation function, and its convolution operation can be represented by equation (6):

$$V_i^k = Relu\left(W_i^{kj} \circledast X_{i-1}^{j} + b_i^k\right) \quad (6)$$

where V_i^k is the kth feature data output from the next layer after the convolution operation, and W_i^{kj} is the weight value of the convolution kernel, and $\circledast$ is the convolution operator, and b_i^k is the bias value of the feature data in the next layer.

(2) The purpose of pooling is to reduce the dimensionality of the feature samples while keeping the number of features unchanged to avoid overfitting. Take the ith feature matrix as an example, let the input feature matrix of the pooling layer be $V_i^k(s,t)$ and its matrix dimension is $s \times t$. The i-th feature matrix obtained after pooling is $C_i^k(m,n)$, whose dimension is $m \times n$, then the maximum pooling operation can be expressed by equation (7):

$$C_i^k(m,n) = \underset{\substack{1+(m-1)Q\le s\le mQ\\1+(n-1)P\le t\le nP}}{Max}\{V_i^k(s,t)\} \quad (7)$$

where P is the length of the pooling window and Q is the width of the pooling window.

(3) Each sample in the 50×3 feature matrix is subjected to two convolution and pooling operations, and is able to produce j feature matrices of dimension m×n. The above feature matrix is subjected to PCA dimensionality reduction to reduce the covariance of the sample features and avoid the influence of redundant features, thus reducing the training time of the LSTM long and short-term memory network, so that the whole CNN model finally outputs a feature vector Xt = {x1 , x2 , ... , xi , ... , xj , }

3.2.2 Long Short Term Memory (LSTM) Network

CNN convolutional neural networks are able to mine local spatial features related to brake pad wear, but it is difficult to extract longer time series data, so this paper uses LSTM long and short term memory networks to further process the feature vectors output from CNN models to construct the link between sample features and time series. lstm networks were proposed by Hochreiter and Schmidhuber in 1997 proposed in 1997[16] , the principle of which is as follows:

(1) Through the forgetting doorf_t The state of the previous level of units C_{t-1} Performing forgetting or memory processing;

(2) By input gatei_t The input sample features areX_t A logical calculation is performed to update the memory of the whole system, which is transmitted according to the path set by the system to generate a new memory featureC_t The calculation of the new memory feature Ct constructed by the input gate and the forgetting gate can be expressed in equation (8):

$$C_t = f_t \otimes C_{t-1} + i_t \otimes tanh(H_{t-1}) \quad (8)$$

(3) Output gateso_t Memory featuresC_t The timing features are output by a control operationH_t and transfer to the next layer of cells, the timing characteristicsH_t The calculation can be expressed in equation (9):

$$H_t = o_t \otimes tanh(C_t) \quad (9)$$

Following the above principle is able to extract the temporal features of the samples, and its LSTM network structure is shown in Figure 4.

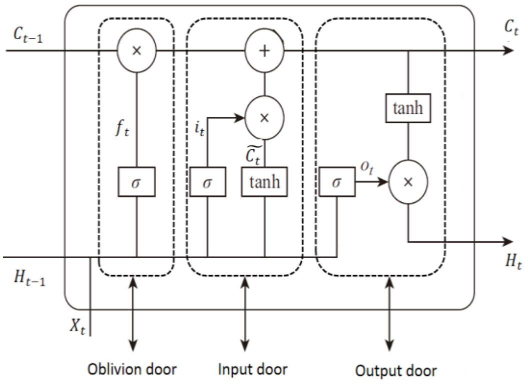


Figure 4 LSTM network gate cell structure

3.2.3 LSTM model based on attention mechanism

The CNN-LSTM model proposed above can achieve deep mining of brake pad wear features in space and time, and has obtained strong generalization ability and faster network fitting speed, but there is still room to improve the accuracy of the model. The attention mechanism can give different weight values to each feature according to the significance of the sample features, thus avoiding the interference of invalid features and improving the prediction accuracy of the model [17]. The attention mechanism based LSTM network model is shown in Figure 5.

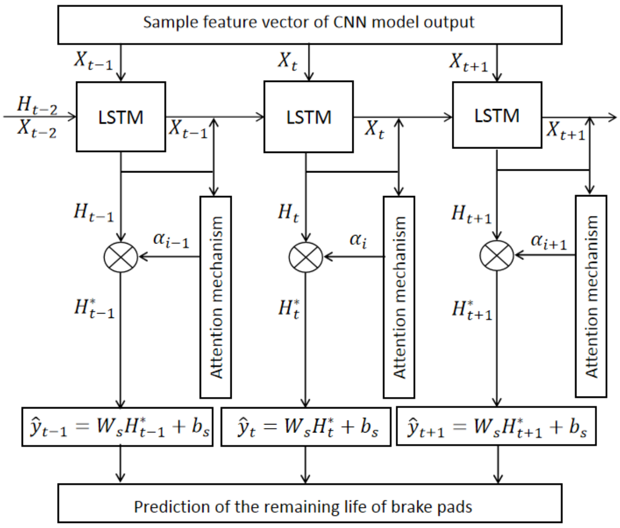


Figure 5 LSTM model based on attention mechanism

The specific principle of the LSTM network model based on the attention mechanism is as follows:

(1) Decode the hidden layer state of the input brake pad wear feature Xt for each Δt time $H_{t,i}$ and then apply theAttention_Score function to compare the hidden layer states $H_{t,i}$ with the output of the LSTM network H_t correlation of the LSTM network, and the score of each sample feature at each Δt time is calculated$E_{t,i}$ which is calculated as shown in equation (10):

$$E_{t,i} = Attention\_Score(H_{t,i}, H_t) \quad (10)$$

(2) Based on the scores of each sample feature at each Δt time, a softmax function was used to value the attention weights of the input brake pad wear featuresα_i were calculated as shown in equation (11);

$$\alpha_i = \frac{exp[Attention\_Score(H_{t,i}, H_t)]}{\sum_{j=1}^{m} exp[Attention\_Score(H_{t,j}, H_t)]} \quad (11)$$

(3) The attention weights of the brake pad wear features areα_i with the output of its LSTM networkH_t weighted aggregation operation, resulting in a new brake pad wear feature vector H_t^* which is calculated as shown in equation (12):

$$H_t^* = \sum_{i=1}^{m} H_t * \alpha_i \quad (12)$$

where m is the number of nodes in the output of the fully connected layer.

In summary, the weight calculation process of the attention mechanism is implemented through the attention layer, the input of which is the temporal feature vector extracted by the LSTM networkH_t and the output is a feature vector of H_t^* The new brake pad wear feature vector H_t^* The new brake pad wear feature vector is input to the fully connected layer to predict the remaining brake pad life and obtain the brake pad wear value $\hat{y}_t$ The new brake pad wear feature vector is input to the full connection layer to complete the prediction of the remaining brake pad life. It is calculated as shown in equation (13):

$$\hat{y}_t = W_s H_t^* + b_s \tag{13}$$

where $\hat{y}_t$ is the predicted value of brake pad wear, the$W_s$andb_s are the weights and bias values of the fully connected layer, respectively.

3.3 CNN-LSTM-Attention Model prediction process

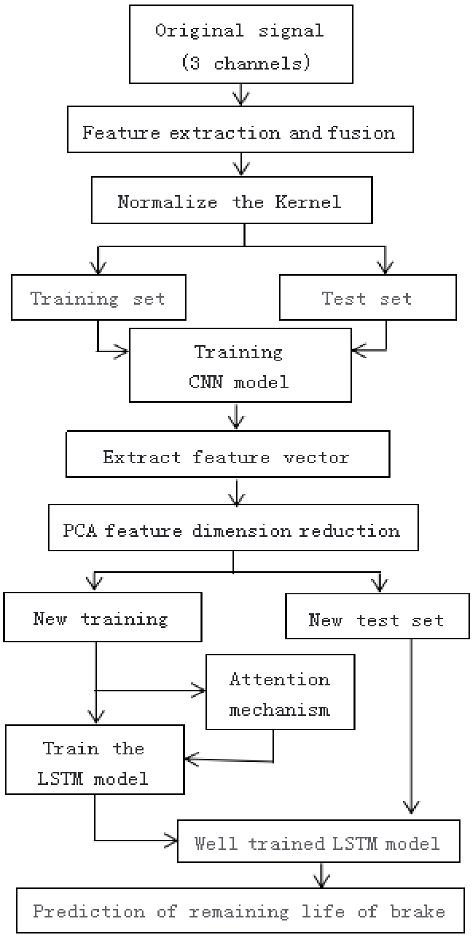


Figure 6 CNN-LSTM-Attention Model prediction process

The CNN-LSTM based Attention model for regression prediction of the remaining brake pad life contains the following six steps, feature extraction and processing, division of sample data, training of CNN model, training of LSTM model, weight assignment of attention mechanism and prediction of brake pad wear, the CNN-LSTM-Attention model prediction process is shown in Figure 6, and the specific steps are as follows:

(1) Feature extraction and fusion of the raw signals from the 3 channels of brake speed, brake pressure and brake temperature as well as brake pad wear values to form a 50 x 4 sample matrix.

(2) The above 50×4 sample matrix was batch normalised and its order was randomly disordered to divide the training and test sets of the CNN model in a ratio of 3:2.

(3) The CNN network is constructed, and the training and test sets from step 2 are used to perform convolution and pooling operations to extract a spatial feature vector Xr, which is dimensionally reduced by PCA to form a new training and test set.

(4) Construct an LSTM network and apply forgetting gates, input gates and output gates to the training set output from step 3 to extract a temporal feature vector Ht.

The attention mechanism is introduced to assign weights to each wear feature, eliminate invalid features, output a new wear feature vectorH_t^* and complete the training of the LSTM model.

The test set output from step 3 is fed into the LSTM model trained in step 5 to complete the regression prediction of the remaining brake pad life.

4 Experimental analysis of brake pad life models

4.1 Setting of structural parameters of the prediction model

Based on the advantages of Convolutional Neural Network (CNN) in mining spatial features and the characteristics of Long Short Term Memory Network (LSTM) in processing temporal features, this paper proposes an Attention-CNN-LSTM based brake pad life prediction model. After comparing the experimental prediction effects, the optimal model structure and parameter configuration selected in this paper is shown in Table 2, which mainly includes an input layer, CNN layer, LSTM layer, Attention layer, Dropout layer and output layer. The model first passes a 50×4 sample dataset through the input layer to the CNN layer, which mines the deep features of the brake pad wear data and uses them as input to the LSTM layer after two convolutions and pooling. The LSTM layer then learns the non-linear relationship between brake pad wear and the input features as well as the time dependence present in the brake pad wear sequence. Finally the attention mechanism uses a scoring function to assign greater weight values to the brake pad wear features at important moments, and the output layer is used to obtain the brake pad wear prediction values. Thus, the essence of the model is in obtaining a mapping between the current moment's brake pad state and the brake pad wear values at multiple historical moments.

Table 2 Structural parameters of CNN-LSTM-PSO model

1	Input layer	Sample data set Matrix dimension: 50 x 4
2	Convolutional layer 1	Activation function: RELU Convolution kernel: 3 x 3 Maximum pooling
	Batch standardisation layer 1	
	Pooling layer 1	
3	Convolutional layer 2	Activation function: RELU Convolution kernel: 3 x 3 Maximum pooling
	Batch standardisation layer 2	
	Pooling layer 2	
4	LSTM layer	Learning rate: 0.004 Number of hidden layer units: 50 Activation function: Sigmoid
5	Attention layer	Attention weighting values: α_i Scoring function: Attention_Score
6	Dropout layer	25% discard
7	Output layer	Activation function: Softmax

4.2 Comparison of predictive model evaluation indicators

In order to quantify the predictive performance of the brake pad residual life model, three objective evaluation metrics are selected, namely the mean absolute error MAE, root mean square error RMSE and coefficient of determination R2. The mean absolute error MAE can be used to obtain an evaluation value, but a comparison between different models is required to reflect the model's merit. The smaller the RMSE and the closer the coefficient of determination R2 is to 1, the higher the accuracy and precision of the prediction model. The three evaluation indicators are calculated as follows:

$$MAE = \frac{\sum_{t=1}^{m}|y_t - \hat{y}_t|}{m} \tag{14}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{m}(y_t - \hat{y}_t)^2}{m}} \tag{15}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{m}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{m}(y_t - \bar{y})^2} \tag{16}$$

where, m is the number of samples output from the fully connected layer, the number of samples in this paper is 50, and $\hat{y}_t$ is the predicted value of brake pad wear, and y_t is the actual value of brake pad wear.

4.3 CNN-LSTM-Attention Model prediction results

The CNN-LSTM-Attention model proposed in this paper is verified by using the data published by the Disc Brake Simulation Experimental Research Group of China University of Mining and Technology [18]. The data set was experimented using a disc brake simulated braking test bed, where information from three channels of braking speed, braking pressure and braking temperature were collected using each sensor at Δt time intervals, while the wear thickness of the brake pads was measured. The data set was feature extracted and fused to form a final 50 x 4 sample matrix, which was fed into a CNN-LSTM model based on an attention mechanism to perform regression prediction of the remaining life of the brake pads, the prediction results of which are shown in Figure 7. The average absolute error MAE value of the model is 0.0048, the root mean square error RMSE value is 0.0059 and the coefficient of determination R2 value is 0.9636. The results show that the CNN-LSTM model based on the attention mechanism can effectively predict the remaining life of brake pads and achieve better results.

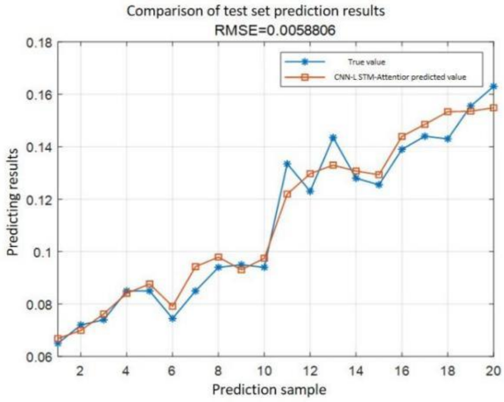
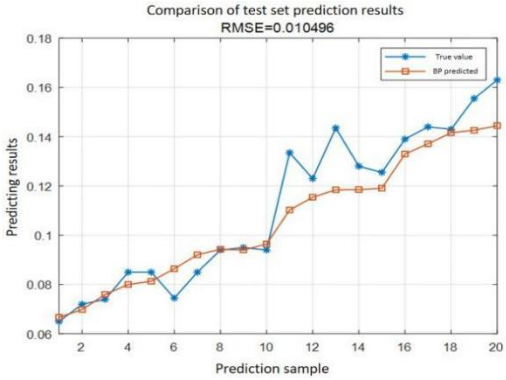


Figure 7 CNN-LSTM-Attention model prediction results

In order to further validate the prediction performance of the CNN-LSTM brake pad residual life model based on the attention mechanism, a comparative analysis with other traditional prediction models in the past, such as BP neural network, CNN model, LSTM model and CNN-LSTM model, was carried out. Figure 8 shows the comparison results of the four traditional life prediction models. From Figure 8, it can be seen that the CNN-LSTM-Attention model proposed in this paper has 43.8%, 35.2%, 29.8% and 16.9% lower RMSE values compared to the BP, CNN, LSTM and CNN-LSTM models respectively; and the CNN-LSTM-Attention model predicts a brake pad wear curve that is closer to the real brake pad wear curve than the other four prediction models, and the error curve has the smallest fluctuation range.

It can be seen that the prediction performance of the CNN-LSTM brake pad remaining life model based on the attention mechanism proposed in this paper has certain superiority. This is because other traditional prediction models have a single algorithm and incomplete feature extraction, while the CNN-LSTM model is not only capable of mining deep spatial features, but also better able to handle temporal features; at the same time, different weight values are given to the brake pad wear data at different moments in the input sample under the action of the attention mechanism, which strengthens the attention to the wear data at key moments in order to more accurately represent the brake pad This results in a more accurate representation of the brake pad wear feature information, thus making the generalization ability of the whole model stronger and further improving the accuracy of brake pad wear prediction.



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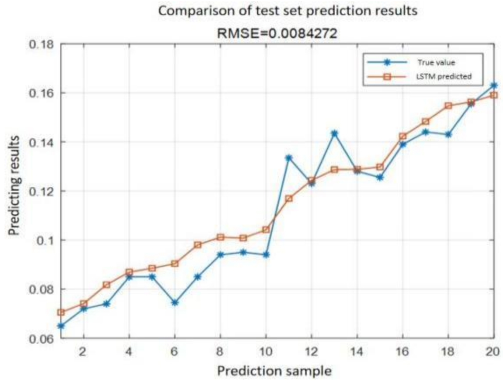

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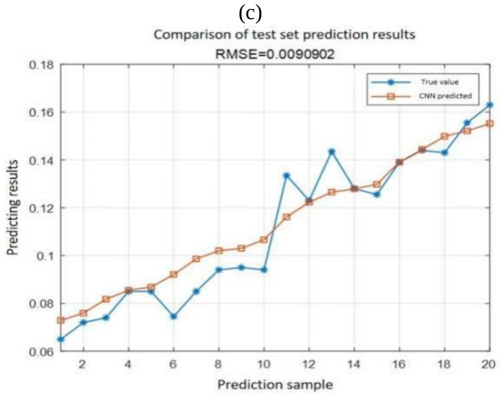
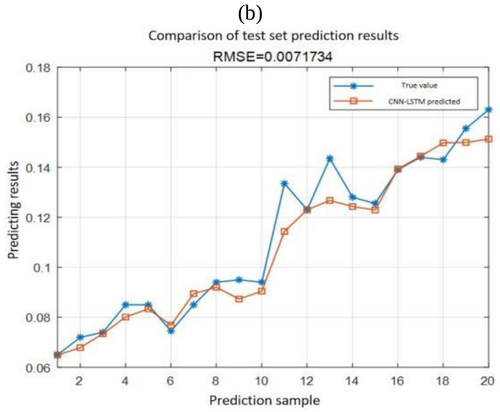


(b)



(d)

Figure 8 Prediction results of the four traditional models

(a) BP model (b) CNN model (c) LSTM model (d) CNN-LSTM model

Table 3 shows the calculation results of the five model evaluation metrics. Compared with the improved CNN-LSTM model based on the attention mechanism proposed in this paper and the CNN-LSTM model, the mean absolute error MAE and root mean square error RMSE are reduced and the coefficient of determination R2 was improved, This result demonstrates the role of the attention mechanism in predicting brake pad wear. In addition, compared with other traditional prediction models, the CNN-LSTM-Attention The mean absolute error MAE of the prediction model was the smallest, with a reduction of 37.7%, 31.4%, 28.4% and 2.04% compared to the BP, CNN, LSTM and CNN-LSTM models respectively; the value of the coefficient of determination R2 was closest to 1, with an improvement of 8.26%, 5.25%, 3.99% and 1.85% , respectively, these two results again prove that using the CNN-LSTM-Attention The two results again demonstrate that the CNN-LSTM-model proposed in this paper is more accurate in predicting the brake pad thickness wear value, and can be more effective in monitoring and intelligently warning the remaining brake pad life.

Table 3 Comparison results of the five model evaluation indicators

Lifetime prediction models	RMSE	MAE	R2 Value
BP Neural Networks	0.0105	0.0077	0.8840
CNN models	0.0091	0.0070	0.9130
LSTM model	0.0084	0.0067	0.9252
CNN-LSTM Models	0.0071	0.0049	0.9458
CNN-LSTM-Attention model	0.0059	0.0048	0.9636

5 Conclusion

In this paper, we use sensor technology to collect the raw signals from 3 channels of brake speed, brake pressure and brake temperature, and also measure the wear thickness of brake pads, and construct a sample matrix after feature extraction and fusion, then propose a CNN-LSTM prediction model based on attention mechanism to predict the remaining life of brake pads, and conduct a comparative study with other traditional prediction models, the results show that:

(1) With the increase of braking speed, braking pressure and braking temperature, the amount of brake pad wear of the car is on the rise; however, braking speed and braking temperature have a greater influence on the amount of brake pad wear, while braking pressure has no significant influence on the amount of brake pad wear.

(2) Using the CNN-LSTM-Attention model for regression prediction of brake pad wear values with a mean absolute error MAE value of 0.0048, a root mean square error RMSE value of 0.0059 and a coefficient of determination R2 value of 0.9636, which indicates that the model can effectively predict the remaining life of brake pads with good results.

(3) Compared with the BP model, CNN model, LSTM model and CNN-LSTM model, the CNN-LSTM-Attention model proposed in this paper mean absolute error MAE and root mean square error RMSE values were reduced, and the value of the coefficient of determination R2 was improved to be closest to 1. This indicates that the constructed brake pad life prediction model has less error, better accuracy and better results.

In the future, the CNN-LSTM -Attention brake pad residual life prediction model can be widely used in automotive manufacturing and car maintenance, etc. The model is of practical significance as it monitors the brake pad braking speed, braking pressure and braking temperature in real time, outputs the wear of the brake pad after each braking, and accumulates the wear after braking to calculate the remaining thickness of the brake pad, and generates a failure alarm indication when the remaining thickness of the brake pad exceeds the wear threshold to avoid accidents caused by brake failure.

Author Contributions: For Conceptualization, methodology, analysis, and writing original draft preparation, Wang Shuo; writing review and full-text editing, Yu Zhenliang; writing — original draft preparation, Xu Guangchen; writing — original draft preparation, Chen Sisi.

Conflicts of interest: The authors declare no conflict of interest.All authors have read and agreed to the published version of the manuscript.

Acknowledgments: The research work financed with the means of Liaoning Provincial Science and Technology Department natural Science Regional Joint Fund project, No.2022-YKLH-03.

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