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Safety Detection and Risk Early Warning Model for Bridge Health Monitoring Based on Neural Network Algorithm

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ABSTRACT
Aiming at the bridge project in the construction of the development of the status quo of the overdevelopment, maintenance and management level lagging behind, this paper, under the premise of ensuring the safety of the bridge, the bridge surveillance monitoring and risk early warning launched a study to solve the problems of its operation and repair and maintenance. For bridge monitoring and safety monitoring, this paper is based on the vibration acceleration of bridge structure damage identification. On this basis, the damage recognition model constructed by using common neural networks convolutional neural network (CNN), long short-term memory network (LSTM) and deep autoencoder (DAE), and the recognition effect of the three models is compared. This for, for the bridge risk problem, this paper utilizes the Extreme Learning Machine (ELM) and Firefly Algorithm (GSO), constructs the implementation of the GSO-ELM algorithm model for early warning of the bridge safety risk, and the experimental results show that the model proposed in this paper has good effect, which provides support for the future development of the bridge structural safety facilities should be developed in the direction of digitization, automation, and networkization.

Keywords: neural network, baseline learning machine, firefly algorithm, damage identification, risk warning

1. Introduction

Bridges are large-scale infrastructures with huge investment and long service life, so the safety of their use plays a pivotal role for the bridges themselves and the national economy [1-2]. In the course of its operation, due to adverse factors such as loading, fatigue effect and material aging, the bridge structure will inevitably produce aging phenomenon, damage accumulation, and even lead to sudden accidents [3-5]. For this reason, health monitoring of bridges and other large-scale infrastructure can grasp the

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health status of bridges at any time, so that the maintenance and repair work of bridges is more theoretically guided [6-8].

Bridge health monitoring is a complex systematic project, in which the accuracy of monitoring equipment, structural signal acquisition and environmental interference, signal processing and analysis, structural damage identification algorithms and other factors may cause structural damage and evaluation of the larger deviation [9-12]. Bridge health monitoring mainly includes the monitoring of important parameters such as the geometry of the main bridge components, material mechanical properties, and displacement and deformation, structural stress and deformation, structural nonlinear properties, and even the online monitoring of the external environmental factors of the bridge [13-16]. Through the real-time monitoring and analysis of these data, bridge failures and diseases can be detected in time to improve the safety of bridges [17-18]. In practical engineering applications, due to the slow development of the cumulative structural damage, the structural response signal is then weakly changed, the bridge health monitoring system should be selected by considering the accuracy of the monitoring equipment and the structural damage-induced static and dynamic response quantitative value for matching [19-22]. When the structural static and dynamic response caused by damage is comparable to the level of environmental noise and equipment measurement error, it is often difficult for the bridge health monitoring system to obtain ideal monitoring results, so the application of big data and artificial intelligence technology in bridge health monitoring has been emphasized to solve the problems of insufficient computational power and inefficiency of the analysis method [23-26].

Literature [27] examined the current status and future trends of bridge monitoring, proposed AI-based data processing methods, summarized the performance prediction and early warning systems, and discussed the challenges and future research directions of structural health comprehensive monitoring (SHM) systems. Literature [28] proposed a batch-based bridge health condition monitoring and early warning system with wireless and low-cost features and an early warning system to reduce bridge maintenance costs, extend life and improve transportation safety. Literature [29] reviewed the challenges associated with bridge health monitoring, pointing out that deformation, fatigue, and corrosion are all factors that contribute to the long-term degradation of bridges, and explored issues related to wireless sensor drift, aiming to help novices in order to identify damages using data collected by sensors installed in real structures. Literature [30] explores the development of bridge health monitoring in recent years, outlining the strengths, weaknesses and research directions of current research in this area, aiming to provide a framework and methodology for future research. Literature [31] describes the application process of Global Navigation Satellite System (GNSS) dynamic deformation monitoring, the development of GNSS deformation measurement techniques in bridge health monitoring, dynamic characteristic identification methods and their applications in bridge GNSS monitoring, and looks forward to future research and applications. Literature [32] developed an IoT based bridge safety monitoring system using wireless sensor network technology to collect data such as weather conditions, sound, air quality, and so on, thus realizing bridge condition monitoring. Literature [33] collated the monitoring parameters and characteristics of different sensor systems, outlined the factors to be considered during sensor calibration and the challenges faced by the current technology, and suggested research trends for bridge monitoring sensor calibration, aiming to provide a reference for practical research on bridge sensor calibration. Literature [34] emphasizes the important role of monitoring and tracking structural damage of bridges, describes the application of advanced techniques such as LiDAR, photogrammetry, computer vision, and machine learning in BHM operations, and outlines these state-of-the-art BHM technologies.

In this study, the bridge operation and cover problems are investigated from two perspectives of bridge safety monitoring and risk early warning. Firstly, in terms of safety monitoring, this paper recognizes bridge damage based on vibration acceleration, and chooses wavelet threshold decomposition as the noise reduction method of bridge vibration signal. Then CNN, LSTM and DAE are used to construct a damage identification model, and the damage identification effect of the model is studied. On the other hand, this paper establishes a GSO-ELM algorithm model for risk prediction based on ELM and GOS, and verifies the prediction effect of the model through examples. It is proved that the method of this paper can effectively identify the bridge damage for the bridge, and at the same time, it can effectively predict the deformation risk, so that effective pre-control measures can be taken in bridge maintenance and repair.

2. Bridge health monitoring safety inspection

At present, bridges are important hubs of urban transportation, and scientific maintenance and management of bridges to ensure the safe operation of various types of bridges is an urgent need for the development of urban economic construction, and is increasingly receiving attention from all walks of life. In addition to the recent serious damage to bridges at home and abroad, even the collapse of the incident, so that the scientific research around the bridge maintenance and management has become the international scientific and technological community, engineering research hot spots. In view of the concept of bridge management, maintenance personnel should carry out real-time monitoring of their own bridges, and long-term collection of bridge health information, so as to achieve early detection, early measures to ensure the health and safety of the bridge operation. This poses a problem to bridge maintenance, if each bridge needs to be tested and analyzed for various parameters, it is bound to invest a lot of manpower to carry out monotonous and repetitive work, and it may also seriously affect the normal passage of vehicles on the bridge.

Due to the complexity of the urban geographic environment, traffic forms, coupled with the requirements of the bridge structure is not limited to the use of its function, a considerable number of factors into account to the aesthetic, and environmental coordination, and so on, and thus the form of the urban bridge form different. At present, the bridge type often found in the city can include cable-stayed bridges, tie arch bridges, beam bridges, concrete arch bridges, steel bridges and so on. They have beams, towers, cables (or ties), arches and piers and other major components. In order to realize the real-time monitoring of the bridge by the maintenance personnel, it is necessary to install a variety of testing equipment on each bridge, use the network to connect the bridges. And ultimately connected to the central control room, the central control room of each bridge for unified monitoring. Alarms are issued for bridges with potential safety hazards, and the relevant data collected can also be used for leadership decisions on urban planning (e.g., traffic counts, etc.). Moreover, the use of bridge network for unified monitoring of bridges can also greatly reduce the work intensity of maintenance personnel and improve work efficiency.

2.1. Limitations of traditional bridge health monitoring

Traditional bridge maintenance is based on evaluating the safety and durability of current bridge structures using information obtained from manual visual inspection or portable instrument measurements. However, when specifically implemented, it has certain limitations, which are mainly manifested as:

1) Manual inspection consumes manpower, material resources and has inspection blind spots. Especially for large bridges, the current detection technology is usually based on manual visual inspection or portable instrument measurement, so it requires a lot of manpower, and in accordance with the specifications of the inspection program for the manual scoring is subjective and difficult to quantify.

2) The detection program lacks integrity. The object of traditional inspection is generally a single component, so each inspection can only provide a single component of the test results, can not make a comprehensive diagnostic assessment of the overall situation of the bridge.

3) Affecting normal traffic operation. When large bridges are inspected for maintenance, observation platforms or inspection vehicles are usually set up. Therefore, it will generally do traffic restrictions on the inspected bridge.

4) Long inspection cycle, poor timeliness. Generally, large bridges are inspected periodically, and thus real-time inspection of the current bridge status cannot be achieved.

Therefore, with the traditional inspection procedures and facilities, in addition to the waste of resources, the most important problem when monitoring the safety of bridges is the monitoring process of spatial and temporal discontinuity. The current monitoring of bridges is no longer satisfied with a certain stage of construction, but spans the entire life cycle of bridge construction, and this discontinuity directly leads to the difficulty of comprehensive coverage of the safety monitoring work.

In order to eliminate the discontinuity of bridge monitoring and realize the full coverage of bridge structural safety management, this paper optimizes the safety and health monitoring of bridges from the two aspects of bridge structural damage identification and bridge safety risk warning.

2.2. Neural Network Based Bridge Damage Recognition

2.2.1. Damage identification of bridge structures based on vibration acceleration. The traditional signal analysis methods mainly focus on signals that are smooth, while the bridge health monitoring system collects often non-smooth signals, so they need to be further analyzed. In order to be able to simultaneously observe the transformations of the signal in the time and frequency domains, researchers have proposed a time-frequency analysis method. The wavelet transform (WT) is an adaptive time-frequency domain analysis method, which is special in that by segmenting the signal using a telescoping and panning algorithm in a time window, the high and low frequency portions of the signal can be refined at multiple scales, respectively, so as to locally analyze the time-frequency signals and to highlight the characteristics of the signal in a particular aspect. Therefore, according to the different stretching and shifting operations, wavelet transform is also divided into continuous wavelet transform (CWT) and discrete wavelet transform (DWT).

Assuming that the function of a signal is defined as $f(t)$, there exists a space where functions $\psi(t)$, $\psi(t) \in L^2(R)$, $L^2(R)$ are square productable and satisfy the Fourier transform, which is called the wavelet mother function:

$$\int_{-\infty}^{+\infty} \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty \tag{1}$$

A telescopic translation transformation of this wavelet parent function yields the wavelet basis function $\psi_{a,b}(t)$, see Eq:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \tag{2}$$

where a is the expansion factor, and $a > 0$, corresponds to the frequency and satisfies the inverse relationship. b is the translation factor, and $b \in R$, mainly controls the position of the wavelet function on the time axis. The continuous wavelet transform is defined as:

$$W_f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t) \hat{\psi}\left(\frac{t-b}{a}\right) dt = < f(t), \psi_{a,b}(t) >, a \neq 0 \tag{3}$$

where $\hat{\psi}(\omega)$ is the Fourier transform of the wavelet basis function $\psi(\omega)$.

In the time-frequency analysis of the continuous wavelet transform coefficients of the redundancy is large, often lead to too much computation, in order to overcome this problem, in the processing of real signals often use discrete wavelet transform, which is discretized by the wavelet basis function to minimize the amount of redundancy in the wavelet analysis. The specific operation is to discretize the telescopic translation factor $\{a,b\}$, so that $a_0 = a$, $b_0 = b/n$, $a_0 > 0$, $b_0 > 1$, $m \in Z$. Then the wavelet basis function $\psi_{m,n}(t)$ is defined as:

$$\begin{aligned}\psi_{m,n}(t) &= a_0^{-m/2}\psi\left[a_0^{-m}\left(t - na_0b_0\right)\right] \\ &= a_0^{-m/2}\psi\left(a_0^{-m}t - nb_0\right)\end{aligned} \tag{4}$$

Therefore, its discrete wavelet transform is:

$$W_f(m,n) = a_0^{-m/2}\int_{-\infty}^{+\infty} f(t)\hat{\psi}\left(a_0^{-m}t - nb_0\right)dt \tag{5}$$

In this paper, wavelet threshold decomposition is chosen as the noise reduction method for bridge vibration signals. In the actual bridge structure monitoring process, when the bridge is damaged, the vibration response data associated with it will also change, and the response data received by the sensors are often high-dimensional data on different monitoring points, so this paper adopts (Principal Component Analysis) PCA to process the vibration data and use the processed data for subsequent analysis.

2.2.2. Deep Neural Network Based Structural Damage Recognition. Deep learning is based on artificial neural networks, which are a basic computational model that tries to make machines learn how to think and learn like humans by simulating the work of neurons in the human brain. A multilayered perceptron that contains several hidden layers is a neural network structure. Artificial neural networks can contain several layers, each layer consists of a number of neurons, neurons are connected to each other by channels with different weights, the input of the neuron is x_i, the output of the neuron is calculated as:

$$y_i = \sum_i \omega_i x_i + b \tag{6}$$

where ω_i denotes the channel weights of the neural network. b is the bias parameter of the neuron.

The training of neural networks usually includes supervised learning, unsupervised learning and reinforcement learning, etc. The most commonly used method is supervised learning, i.e., providing input data and corresponding labels in advance, and allowing the neural network to automatically learn the mapping relationship between the input and the output by iterating through a large amount of data in multiple rounds, and in each training round, the weight parameters are constantly optimized and updated by the back propagation algorithm, so that the prediction results of the neural network are constantly close to the real value. In each training round, the weight parameters are constantly optimized and updated by the back propagation algorithm, so that the prediction results of the neural network are constantly close to the real value.

In this paper, the most commonly used neural network models in deep learning are constructed to identify and analyze the damage of the vibration data from bridge monitoring, and the constructed models include convolutional neural network (CNN), long and short-term memory network (LSTM) and deep autoencoder (DAE), and the specific damage identification process is shown in Figure 1.

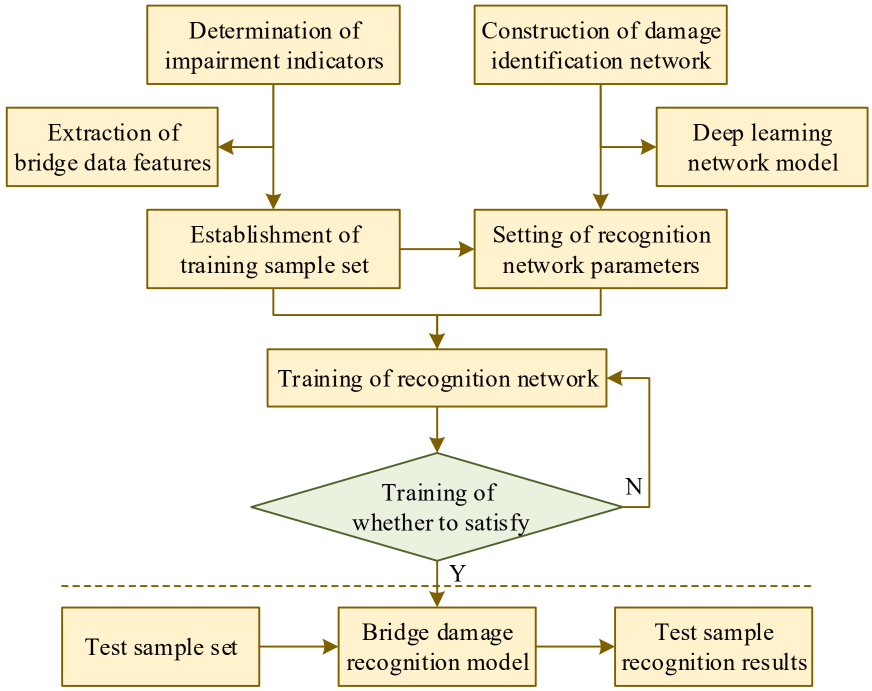

Fig. 1. Bridge structure damage identification process

Convolutional neural network (CNN) is a kind of feed-forward neural network containing convolutional operations, which is able to build a very complex model architecture and continuously improve the ability of the model to express various connections between data, and its hierarchical structure generally contains a convolutional layer, an activation layer, a pooling layer, and a fully connected layer. With the development of deep learning technology, the depth of the convolutional neural network is also increasing, at this time there are some deep convolutional neural networks with simple structure and excellent performance, such as VGG model and ResNet model.

LSTM is a variant of recurrent neural networks that has advantages in its ability to model temporal correlations and accept data of different lengths. By bringing cell states and gate mechanisms into the network, decisions are made about what information should be saved or discarded while overcoming the effects of short-term memory.

The specific structure of the LSTM built in this section is shown in Fig. 2. As can be seen from the figure, this LSTM model includes 200 hidden cells as well as a classification layer, in the hidden cells X_t is the input vector of the current time step, h_{t-1} and h_t are the outputs of the previous and current cells, respectively, and the topmost layers of the information transfer C_{t-1} and C_t are the cell states as a way of learning the long-term dependency information, and the final classification layer consists of two fully connected layers with 128 and 6 neurons, respectively. The activation functions are ReLU and Softmax, respectively.

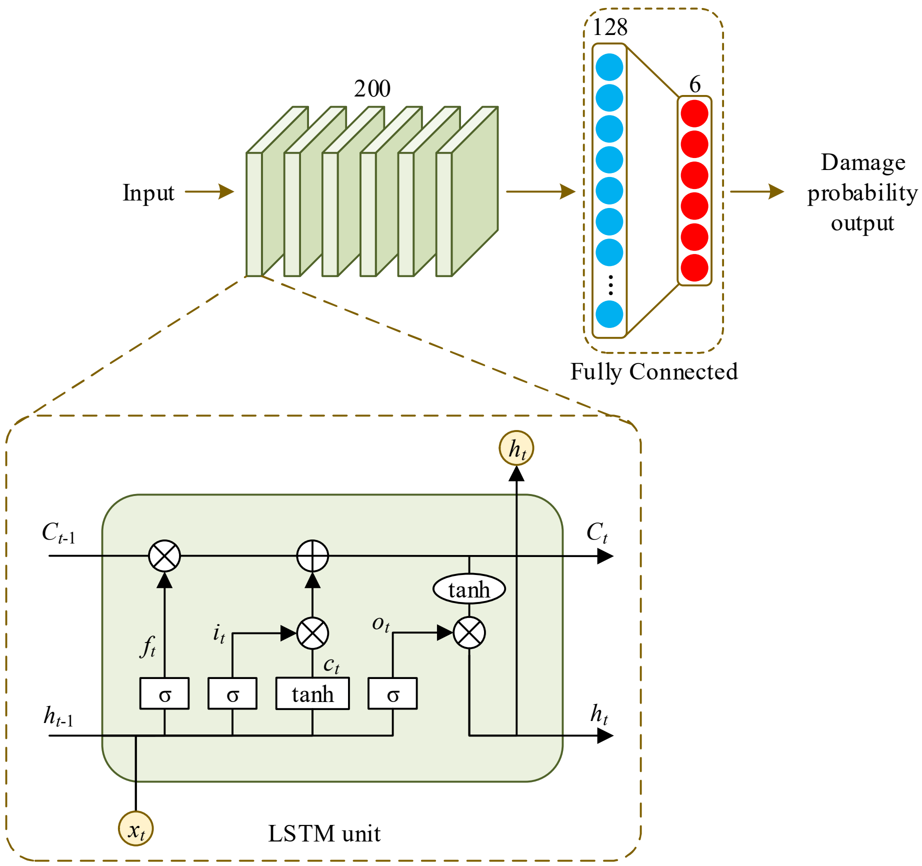

Fig. 2. LSTM model structure

DAE is constructed by stacking multiple self-coding neural networks with the aim of learning mapping relationships through neural networks to reconstruct the input information. The advantage is the ability to extract the implicit information behind the data in an unsupervised manner, providing better generalization ability and prediction accuracy. The autoencoder mainly consists of two parts, encoder and decoder, the role of the encoder is to encode the high dimensional input X into low dimensional hidden variables and the role of the decoder is to reduce the hidden variable h of the hidden layer to the initial dimension, i.e., $X^R \approx X$. The computational process is as follows:

$$h = f\left(\omega^{(1)} X + b^{(1)}\right) \tag{7}$$

$$X^R = f\left(\omega^{(2)} h + b^{(2)}\right) \tag{8}$$

The optimization objective function is:

$$MinimizeLoss = dist\left(X, X^R\right) \tag{9}$$

where $\omega^{(1)}$, $\omega^{(2)}$, $b^{(1)}$, $b^{(2)}$ are the parameters of the autoencoder, which are optimized by training. dist is the loss function, which is usually the mean square error. The DAE model built in this section mainly consists of three encoding layers and three decoding layers, each encoding layer is a fully connected layer with 64, 128, and 256 neurons, respectively, and the activation function is chosen to be Leaky ReLU, and a Batch Normalization layer is connected to each layer for normalization and feature mapping of each batch of data, respectively. After obtaining the initial dimensions a fully connected layer with Softmax activation function is connected to get the final output.

2.3. Bridge Damage Identification Detection Results

In order to investigate the ability of damage features to characterize the damage state of a structure under environmental excitation, this chapter carries out a bridge damage identification study by means of finite element simulation and experimental validation. First, a bridge test model is established, and then a bridge finite element model is built using OpenSees, and the finite element model is corrected according to the modal analysis results. Then, the white noise was used as the excitation to carry out the dynamic time course analysis of the modified finite element model and the test model, to obtain the structural acceleration response, and the four damage characteristics were used as the inputs to carry out the bridge damage identification using the model. Finally, the finite element data is used as the training set and the experimental data is used as the test set for the exploration of bridge span damage identification, which provides a reference for actual bridge damage identification.

The CNN is trained using acceleration features and the loss values and accuracy of the network are obtained as shown in Fig. 3. As can be seen from the loss curves, when the network is trained to 200 epochs, the trend of the loss values in the training set and validation set is consistent, and there is no overfitting phenomenon, which proves that the network completes the training and can be used.

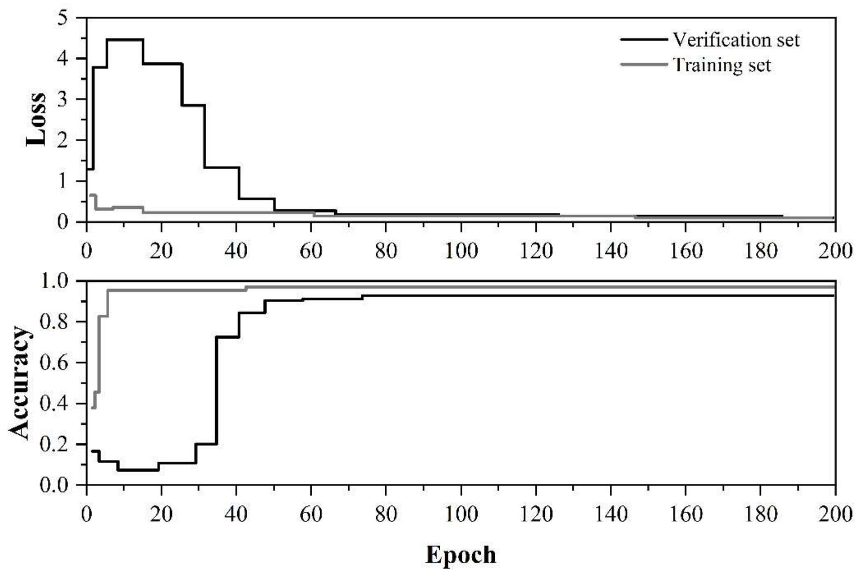

Fig. 3. Tracking of training process parameters based on acceleration

Using statistical features to train the CNN, the loss and accuracy of the network are obtained as shown in Figure 4. As can be seen from the change in loss values, when the network is trained to 200 epochs, the trend of loss change in the training and validation sets is the same, and no overfitting phenomenon occurs, proving that the network completes the training and can be used.

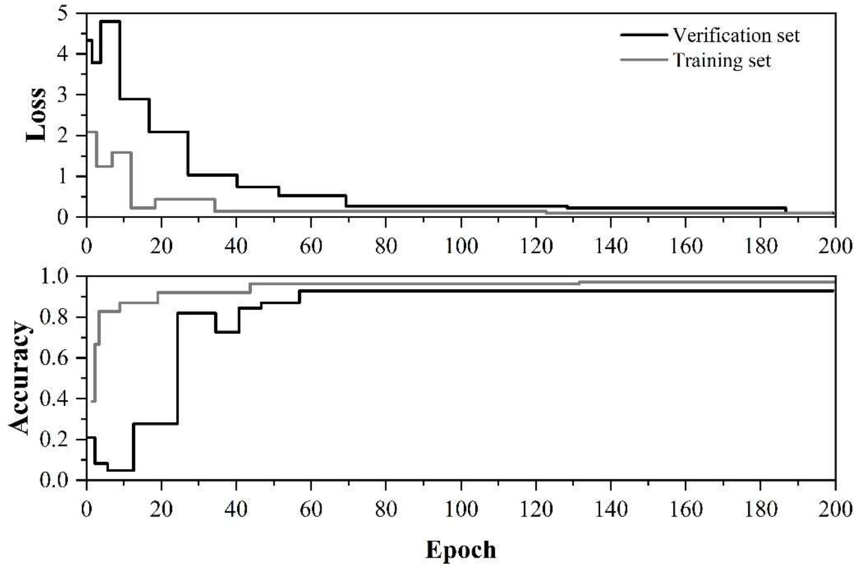

Fig. 4. Tracking of training process parameters based on statistical feature

The CNN is trained using frequency domain features, and the loss curve and accuracy curve of the network are obtained as shown in Fig. 5. When the network is trained to 200 epochs, the trend of the loss change in the training and validation sets is consistent, and there is no overfitting phenomenon, which proves that the network completes the training and can be used.

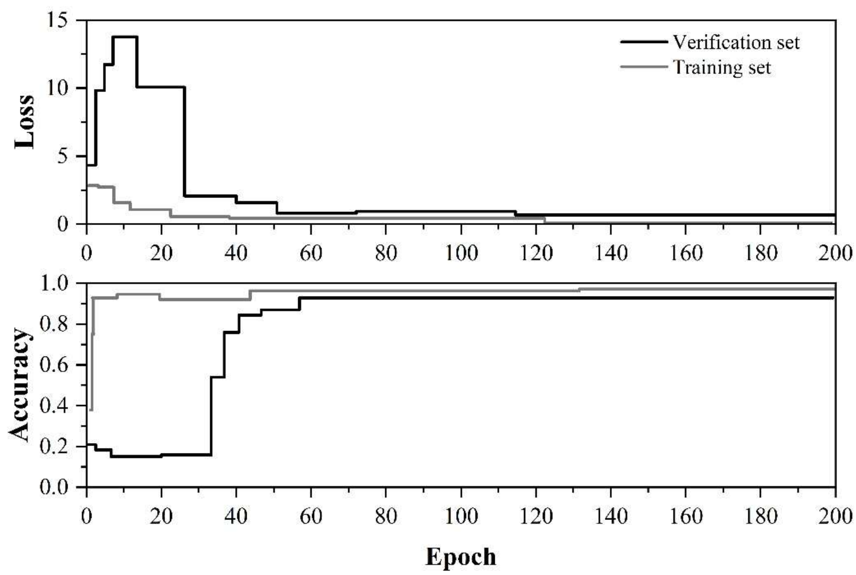

Fig. 5. Tracking of training process parameters based on frequency domain feature

The results of damage identification using acceleration features, statistical features and frequency domain features are shown in Fig. 6, and the comprehensive analysis shows that when using finite element data for bridge damage identification, all three damage features achieve damage identification with high accuracy, and the identification accuracy from high to low is frequency domain features, acceleration features and statistical features, respectively.The average identification accuracy of the CNN model for bridge damage identification is 94.826%, and the average F1 value is 94.800%, which indicates that the CNN model can effectively realize the monitoring of bridge damage and provide an effective basis for bridge safety detection.

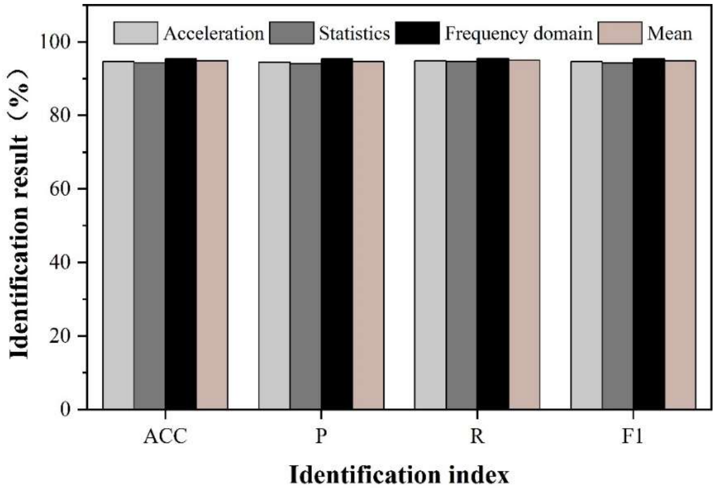

Fig. 6. Damage identification results

Further comparing the damage recognition effect of CNN, LSTM and DAE models, the comparison of loss recognition results of different models is shown in Figure 7. The values of each index of the three neural network models are higher than 92%, indicating that these models have better performance in bridge damage recognition. From the model comparison, the CNN model has the best values of each index in bridge damage recognition, and the accuracy rate (ACC) is 1.284% and 2.670% higher compared to the LSTM and DAE models, respectively.

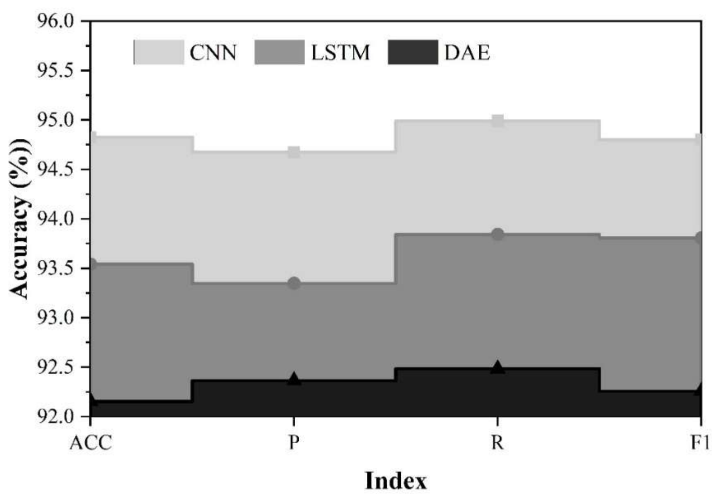

Fig. 7. Comparison of loss identification results of different models

3. Bridge safety risk early warning model

3.1. GSO-ELM risk prediction model

Based on the realization of bridge damage identification, this paper adopts Extreme Learning Machine (ELM) and Firefly Algorithm (GSO) to build GSO-ELM algorithm model to realize the bridge safety risk early warning, and collaborate with the two models to improve the health and safety monitoring of bridges.GSO-ELM algorithm is mainly based on the idea that for the problem of random setting of part of the parameters in the ELM algorithm, GSO algorithm is introduced to find out the optimal parameter setting in the ELM algorithm, thus constructing the GSO-ELM algorithm model with the ability of global search. The main idea of GSO-ELM algorithm is to introduce GSO algorithm with global search capability to find out the optimal parameter setting in ELM algorithm to construct GSO-ELM algorithm model, and the characteristics of GSO algorithm itself, such as simple parameter setting, multi-point parallel processing, and fast operation speed, provide a convenient way for the construction of GSO-ELM algorithm model.

Step 1: Initialization parameters, ELM algorithm part, first select N training samples, its sample set is (x_i, y_i), $i=1,2,\cdots,N$, and then the number of nodes in the implied layer M, excitation function $g(x)$ and other parameters are set, connecting the weights parameter w and bias value parameter b are set randomly, and then run to get the output matrix H to calculate the error value.

In the GSO algorithm part, the initial setting of parameters ρ, γ, β, l_0, n_t, N, s, r_s, r_0, $T_{\max}$ is carried out, and the connection weight parameter w with the bias value parameter b is used as the initial composition of the firefly individuals, then the initial expression of the firefly individuals is $u_i = [w_{11}, w_{12}, \ldots, w_{1n}, \ldots, w_{m1}, w_{m2}, \ldots, w_{mn}, b_1, b_2, \ldots, b_m]$, so that the solution space of the objective function is 2-dimensional. Then all fireflies in the initial population of fireflies are randomly scattered in this 2-dimensional solution space of the objective function. The expected value obtained by running the ELM algorithm is compared with the actual value to find the Root Mean Square Error (RMSE) as the objective function and its inverse as the fitness value of the fireflies.The RMSE formula is expressed as:

$$RMSE = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{M}\left\|\beta jg\left(w_j x_i - b_j\right) - t_i\right\| / N} \tag{10}$$

Step 2: Brightness UpdateAll fireflies are updated with brightness according to the formula.

Step 3: Position update Each firefly searches for fireflies within its respective decision radius, and forms a neighbor set according to the formula if a neighbor individual exists, and updates its own brightness and searches again if it does not exist. When the set of neighbors is established, the probability of its movement towards each target is calculated according to the formula, and the target individual is selected and starts moving in its direction. After moving, update the position according to the formula.

Step 4: Decision Radius Update After updating the position of each firefly the firefly decision radius is updated and its fitness is updated.

Step 5: Determine whether the number of iterations has reached the maximum if the number of iterations has reached $T_{\max}$, then stop the iteration. The output firefly individuals, then the optimal settings of the connection weights parameter w and bias value parameter b.

Step 6: After obtaining the optimal parameter settings for the training of the GSO-ELM algorithm model, input the training samples again for operation and calculate the error value. If the error value meets the requirements, the training is terminated and the final result is output.

Step 7: After the training of the algorithm model is finished, the prediction data can be input to make predictions.The flow chart of the GSO-ELM prediction model is shown in Fig. 8.

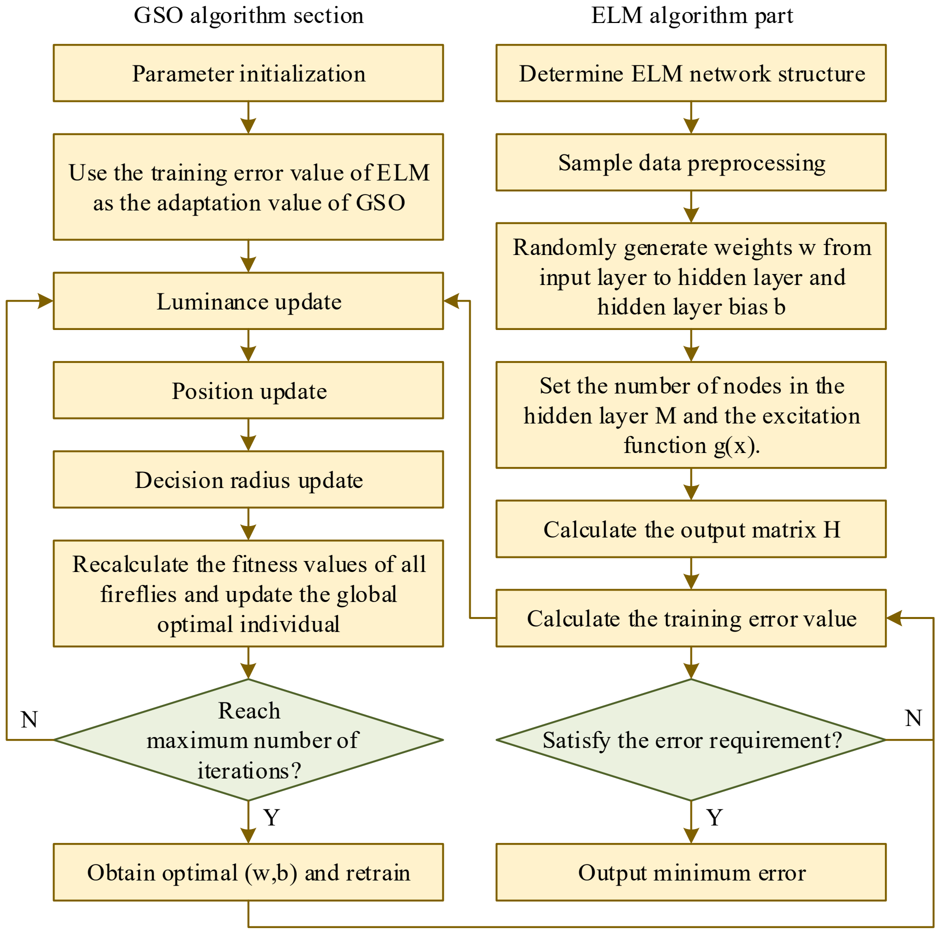

Fig. 8. Flow chart of GSO-ELM model

3.2. Risk of risk prediction results

In order to test the prediction ability of the model, this chapter applies the constructed GSO-ELM algorithm model to the risk prediction example of the bridge safety inspection project, so as to verify the feasibility and practicability of the prediction model, and to provide methodological reference for the bridge risk prediction research. Taking 2 weeks as the prediction cycle, the bridge deformation is predicted, and the prediction results of 10 consecutive days are shown in Table 1. In the prediction results, the prediction accuracies of convergence (C), bulge (H) and lateral deformation (M) are not exactly the same, but their absolute errors are very small, in which the maximum absolute error of convergence deformation is -0.48 mm, bulge deformation is -0.62 mm, and lateral deformation is only 0.36 mm. The prediction results indicate that the error prediction model has good prediction ability, which meets the millimeter-level prediction accuracy requirements. Requirements.

Table 1. Predictive result

Day	Monitoring(mm)			Predictive(mm)			Error(mm)		
	C	H	M	C	H	M	C	H	M
1	6.82	12.48	-1.53	6.83	12.45	-1.53	0.01	-0.03	0
2	7.02	12.68	-1.47	7.02	12.65	-1.50	0	-0.03	-0.03
3	7.02	12.77	-1.56	6.97	12.93	-1.78	-0.05	0.16	-0.22
4	7.12	12.96	-1.47	7.12	12.95	-1.47	0	-0.01	0
5	7.02	12.95	-1.58	7.12	13.19	-1.59	0.1	0.24	-0.01
6	7.42	13.25	-1.72	7.21	12.80	-1.60	-0.21	-0.45	0.12
7	7.42	13.18	-1.65	7.50	12.81	-1.51	0.08	-0.37	0.14
8	7.32	13.31	-1.45	7.57	13.4258	-1.09	0.25	0.1158	0.36
9	7.02	13.29	-1.58	7.06	13.30	-1.53	0.04	0.01	0.05
10	7.12	13.77	-1.45	7.07	13.47	-1.28	-0.05	-0.3	0.17
11	7.12	13.52	-1.61	7.04	13.15	-1.50	-0.08	-0.37	0.11
12	7.22	13.67	-1.73	7.39	13.25	-1.52	0.17	-0.42	0.21
13	7.02	13.7	-1.59	6.54	13.08	-1.54	-0.48	-0.62	0.05
14	7.12	13.79	-1.53	7.30	14.07	-1.73	0.18	0.28	-0.2

In order to further verify the model prediction effect, different locations of the bridge are predicted, and the different locations of the bridge are labeled as QL1~QL10 in order, and the prediction results of the deformation risk of the bridge at different locations are shown in Table 2. From the risk prediction results of different locations, the prediction error is within ±0.1mm, the maximum absolute error is -0.091mm, the maximum relative error is 1.520%, and the maximum relative error corresponds to the tunnel locations of QL2 and QL5. Overall, the relative error of the deformation risk prediction results are within 2%, which shows that the model has a good application of the risk prediction of the bridge. The results show that the model has good application for bridge risk prediction. This shows that the model is effective in predicting the deformation risk of bridges, and then effective pre-control measures can be taken to control the safety risk at a low level.

Table 2. The risk prediction of bridge deformation in different locations

QL	Monitoring data(mm)	Predictive data(mm)	Absolute error(mm)	Relative error(%)
1	1.651	1.655	0.004	0.242
2	0.921	0.935	0.014	1.520
3	0.312	0.315	0.003	0.961
4	2.842	2.862	0.02	0.703
5	11.123	11.032	-0.091	-0.818
6	2.215	2.195	-0.02	-0.902
7	3.121	3.101	-0.02	-0.640
8	3.215	3.212	-0.003	-0.093
9	4.578	4.589	0.011	0.240
10	8.211	8.23	0.019	0.231

4. Conclusion

In this study, the neural network model is used to establish a damage identification model for bridge health and safety, and construct the implementation of GSO-ELM algorithm model for bridge safety risk warning, the main results of the study are as follows:

1) Acceleration features, statistical features and frequency domain features training set and validation set loss value changes did not appear overfitting phenomenon, proving that the network completes the training. The accuracy of the three damage features is higher than 90%, effectively realizing bridge damage recognition. In the model comparison, it is found that the average recognition accuracy of the CNN model for bridge damage recognition is 94.826%, and the F1 mean value is 94.800%, and the accuracy rate (ACC) is 1.284% and 2.670% higher than that of the LSTM and DAE models, respectively. However, on the whole, the values of each index of the three neural network models, CNN, LSTM and DAE models, are higher than 92%, which proves the value of neural network application in bridge damage.

2) In addition, in terms of risk warning, the GSO-ELM algorithm model constructed in this paper has a maximum absolute error of -0.48mm for convergent deformation, -0.62mm for bulge deformation, and only 0.36mm for side shift deformation in the actual prediction, and the risk prediction errors for different locations are all within the range of ±0.1mm, with the maximum relative error only 1.520%, and the relative errors of deformation risk prediction results are all within the range of 2%. The relative errors of the results are within 2%, which shows that the model can effectively predict the deformation risk of the bridge.

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