A. Cheshmehzangi and H. Bilgin (Eds.)

doi:10.3233/ATDE230182

Innovation Research on Construction Safety Management of Civil Engineering Based on Machine Learning

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Abstract. The neural network based on the deep learning theory has a profound theoretical basis and broad application prospects in the field of bridge structure damage identification. The comparison and analysis are made from three aspects of input vector, finite element model and neural network, which provides reference for further research on neural network in bridge structure damage identification. Through analysis, it is found that the ability of neural network to extract relevant information can be effectively improved by selecting the finite element model or the original data obtained in the actual situation as far as possible for the input vector. When the stress of bridge structure is simple, neural network with shallow layers and simple network structure can be selected. When the stress of bridge structure is complex, the neural network model with strong complexity should be selected first.

Keywords. Machine Learning; Civil Engineering; Construction Safety Management

1. Introduction

In recent years, the new generation of artificial intelligence information technology, represented by machine learning, deep learning, and other algorithms, has gradually become the research focus of structural engineering discipline [1]. Especially in the operation and maintenance stage, we have made a lot of valuable and valuable intelligent achievements. However, at the stage of structural calculation and analysis, it is still mainly dependent on solid test and classical finite element technology, and there are problems such as heavy repetitive labour, high dependence on artificial experience, and low calculation efficiency. Although there is a broad and practical demand for intelligence, there are few systematic studies on deep integration of intelligent technology. In the design and construction process of engineering structures, there are inevitably uncertainties in their geometric dimensions, physical properties of materials and boundary conditions, which lead to the randomness of structural resistance. At the same time, the structure also has a certain probability of encountering extreme natural disasters during its service period. These extreme natural disasters have greater randomness, and when its action strength exceeds the resistance limit, it will lead to the direct failure of the structural system. The combination of these two factors makes the

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failure of the structure under natural disasters accidental. Therefore, it is necessary to conduct dynamic reliability analysis on the structure to quantify its failure risk and provide a basis for structural design. Among all kinds of natural disasters, wind disaster is the most common one, which has the characteristics of high frequency, wide impact and large disaster losses.

At present, there are three main frameworks for the application of depth learning theory to bridge structure damage identification: depth convolution neural network, depth self-coding network and long short memory neural network [2]. However, through research and summary, it is found that long-term and short-term memory networks have unique advantages in the field of natural language processing due to the use of gating units. However, since the focus of this model is to judge the relationship between the data before and after, it is not applicable to the loss identification data characteristics of bridge structures in essence. Therefore, based on the comparison of traditional RBF neural networks, this paper constructs the depth convolution and depth self-coding network models for damage identification of bridge structures. As the further development of machine learning, deep learning inherits the good classification ability of neural network, adapts to the nature of pattern recognition of structural damage identification, and has stronger convergence and stability than traditional neural network, which solves the shortcomings of traditional neural network that is easy to fit. At present, there are many problems in the application of depth learning model to bridge damage identification, such as low recognition accuracy, weak anti-noise ability, weak generalization ability, and insufficient practicability. Therefore, this research includes the comprehensive comparison and optimization improvement of the current mainstream algorithm models, and further improves the comprehensive performance of the models. Therefore, we can analyse that the state analysis of the structure during service is a research topic of great social significance. If the research results are greatly developed and actively practiced, it will have a positive significance for personal, property security and social stability [3].

2. Basic Theory

2.1 Machine Learning

Machine learning is to bring information from data. It is the cross field of statistics, artificial intelligence, and computer science, also known as predictive analysis and statistical learning. In daily life, machine learning has been everywhere [4]. When we shop online, Taobao will push us the products we may like; When searching for information, search engines will quickly give matching search results based on the keywords we enter. Machine learning and its branch deep learning have become the focus of discussion. It seems that all problems will be solved if the data are machine learned. However, this is not the case. For the traditional data analysis field, the use of machine learning can really play a good role in predicting market behaviour. However, in some engineering fields, despite many experimental data, machine learning has always been unable to play its part due to poor results, little practical significance, and other factors. Traditional machine learning has been applied in civil engineering. In terms of regression method, linear model, support vector machine and other models can be used to predict the indicators of materials. The strength of ordinary concrete has been clearly specified in the specification, so it is of little significance to use machine learning to predict the strength of concrete. For some materials without specification requirements, such as super early concrete in emergency projects, using support vector machines to learn a small number of laboratory data samples, computers can provide reliable strength prediction, just like experts in this field, to help engineers design the mix proportion of concrete, greatly reducing the risk caused by lack of experience in the application of new materials.

2.2 RBF Neural Network

Radial basis function neural network, also known as RBF neural network, is a more traditional network mode in artificial neural network [5]. Its principle is that the function provides a function set for neurons in the hidden layer using multidimensional strict interpolation method. This function set constructs a basis for transferring the input layer vector to the hidden layer. The functions in this function set are called radial basis functions. RBF neural network is composed of input layer, hidden layer, and output layer. The input layer is composed of original data nodes, connecting the information to be analyzed with the network. The essence of the hidden layer is to use the radial basis function as the transformation function to realize the nonlinear transformation from the input vector space to the hidden layer space, which makes it possible for the neural network to realize the nonlinear calculation; The output layer is a linear combination of hidden layers to provide activation response for the whole network and output certain tag values or vector target features. Generally speaking, there are two methods to determine the initial value of the central parameter: direct selection from the training sample set according to a specific method and determination by clustering. The specific methods are as follows: direct calculation method, self-organizing learning method, supervised learning method, orthogonal least square method. In practice, the hidden layer center of RBF neural network does not use some sample points or sample clustering centers in the training set, but needs to make the neural network center better reflect the information contained in the data set through learning methods. The basic idea of RBF network is to transform the input low dimensional data into a high-dimensional space, so that the low dimensional linear indivisible problems become linearly separable. It has the advantages of high precision, small structure, and fast convergence [6]. It is a locally connected feedforward neural network. The model structure of RBF network is shown in Figure 1.

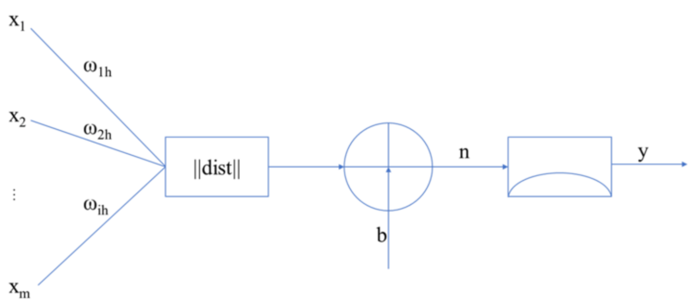

Figure 1. Model structure of RBF neural network.

In Figure 1, b is the threshold value used to adjust the sensitivity of neurons. The activation function of RBF network is mainly determined by the distance named | | dist |

| between the input vector and the weight vector of the network. The general expression of its activation function is:

$$R \parallel dist \parallel = e^{-\parallel dist \parallel^2} \tag{1}$$

As | | dist | | decreases, the output of the network increases. When the neuron output of the network is 1, its input vector is close to the weight vector.

2.3 Deep Convolution Network

Convolution neural network refers to a neural network that uses convolution operation to replace general matrix multiplication operation in at least one layer of the network. Convolution operation is a special linear mathematical operation. Its physical meaning is the weighted sum of a unit response function on the input signal function [7]. CNN combines and stacks different operators in a certain order, extracts abstract features layer by layer, and finally uses these features to complete prediction or classification tasks. The unique convolution and pooling operation process of CNN enables it to obtain transformation invariant features of the input signal, and has natural advantages in processing and learning data with grid features, showing obvious advantages. Generally, the main network layers of a convolutional neural network include convolution layer, pooling layer, and full connection layer. When training the convolutional neural network, if the training samples are few, some regularization methods should be used to avoid the over fitting phenomenon of the model, that is, the error of the model in the training set is very small, while the error in the test set is large. Random deactivation is the most used regularization method in deep neural networks, which improves the performance of neural networks by preventing the interaction of feature detectors. Specifically, after determining the initial structure of the network, Dropout will randomly set part of the neuron responses and the connection between this neuron and other neurons will also be temporarily removed, which can avoid the control effect of high weight nodes on the output results of the neural network, provide more equal learning opportunities for each node, and thus reduce the interaction between hidden layer neurons. At the same time, Dropout is also an efficient integrated learning method. As the deleted neurons cannot participate in the training, the trained neural network is equivalent to a total network of several subnetworks that are integrated averagely, which can effectively improve the generalization performance of the model [8]. The schematic diagram of dropout operation process is shown in Figure 2.

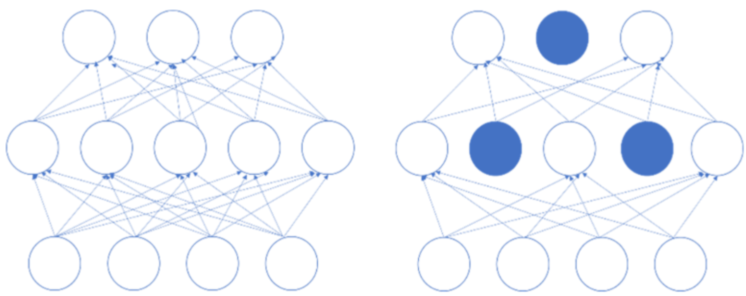

Figure 2. Schematic diagram of dropout operation process.

3. Application of RBF Neural Network in Safety Management of Geotechnical Engineering Construction

3.1 Simply Supported Beam Model

Firstly, the solid model of simply supported beam is established by finite element analysis software. The length of simply supported beam is 1000mm, and the section size is 100mm × 100mm, concrete material, Poisson's ratio is 0.157, density is 2500kg/m3, and elastic modulus under nondestructive condition is 30GPa. Divide 50 units along the length direction. As the structure is symmetrical, only the first 25 elements need to be considered for damage, and the damage condition is simulated by reducing the elastic modulus of damaged elements. The data is divided into training set and test set. The training was concentrated. The degree of injury of each unit was 15%, 30%, 45%, 60%, 75%. There were 25 injury units and 125 groups of data in total. Five units were selected from the test set, and the damage degree was 20%, 35%, 50%, 65% and 75% respectively, a total of 25 groups. After the solid model of simply supported beam is established, the first ten modes are calculated by the subspace analysis method in modal analysis. The first ten natural frequencies obtained are shown in Table 1:

Table 1. First ten frequencies of the nondestructive state of the solid model of the simply supported beam.

Order	1	2	3	4	5
Frequency	148.1	205.1	514.2	605.2	773.6
Order	6	7	8	9	10
Frequency	883.7	1271.1	1305.5	1562.5	1904.4

When the frequency in the undamaged state is taken as the comparison basis, the greater the percentage of damage degree, the greater the change value of frequency. When the structure is damaged, the natural frequency is lower than that in the nondestructive state. The greater the damage is, the faster the decline rate is. When the damage degree reaches 75%, the change rate of the fourth order frequency has decreased by 4.2%, but the change rate of the eighth order frequency is nearly 1%. It can be seen that the change rate of the first and fourth order frequencies is obviously higher than the change rate of the eighth and tenth order frequencies, indicating that the lower order frequencies are generally more sensitive to structural damage [9].

3.2 Continuous Beam Bridge Model

First, a four-span continuous beam bridge is built by using the parametric modeling method of finite element analysis software. Because the continuous beam bridge structure is symmetrical, and considering the influence of damage location on the structure, the damage location is selected to be in the second span, and the node number range is 41-74. Two types of elements are defined, one is beam 4 element and the other is mass 21 element. For the beam of straight section, its elastic modulus is 3.45 × 1010Pa, Poisson's ratio 0.2, density 3300; The elastic modulus of the side fulcrum diaphragm is 3.45 × 1010Pa, Poisson's ratio 0.2, density 2868; For closure diaphragm, its elastic modulus is 3.45 × 1010Pa, Poisson's ratio 0.2, density 2868; The elastic modulus of the diaphragm plate at the middle fulcrum is 3.45 × 1010Pa, Poisson's ratio 0.2, density 2757. For pier material, its elastic modulus is 3.25 × 1010Pa, Poisson's ratio 0.2, density 2650. When defining the main beam section, it is set by defining the real constant r. The parameters involved are number, area, IYY, IZZ, width, height, and torsional inertia moment. In the finite element modelling software, multi-layer nested loops in the command flow are used to realize the gradual movement and change of damage location and damage degree. Due to the symmetrical structure, the first and second order curvature modal values have the same shape and opposite direction. The fourth, fifth, seventh and eighth order modal displacement forms are Z-axial deformation, and the curvature mode cannot represent damage through test analysis; The second, third, fifth and ninth order deformations are Y axial deformations; The tenth mode is X direction displacement of pier. Therefore, we take the second, third, fifth, ninth and tenth order curvature modes as the basis for analysis. Among them, due to the symmetrical structure, the range of nodes numbered 4~39, 74~40 and 76~110 is taken as the analysis basis. For the 45% damage condition at node No. 10, the abrupt change of the first curvature mode is small, and the change of the second, third and fourth curvature is large. It shows that the low order curvature mode and the high order curvature mode are less sensitive to damage, and the second, third and fourth order curvature modes in the middle are more sensitive to damage [10].

3.3 Arch Bridge Model

According to the engineering documents, the double span arch bridge is established. The length of the beam is 32.5m, which is a symmetrical structure. The number of beams in each span is 18, and the spacing is 6.25m. The middle longitudinal beams are located at the mid span of the beam, 6.14m from the mid span, and 12.6m from the mid span. Considering the actual situation, the damage location is set on the single side suspender of the first span. The established finite element model is shown in the Figure 3:

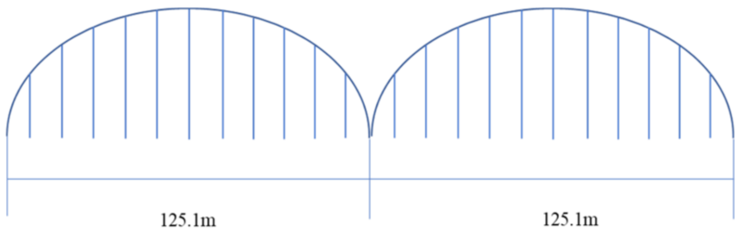

Figure 3. Span diagram of arch bridge.

As for continuous bridges, five levels of damage degree are set: 15%, 30%, 45%, 60% and 75% on the training set, the elastic modulus without damage is 3.0e10, and the damage degree on the test set is 20%, 35%, 50%, 65% and 75%. In this data set, it is assumed that the suspenders numbered 1-17 are damaged There are 90 sets of data sets in total. From the first ten modes of the arch bridge finite element model, the changes of the first four modes are mainly reflected in the pier, so the location value extracted from the principal axis direction may not represent the damage. Therefore, only the tenth mode value of the fifth mode is taken as the basis for analysis, and the following numbers are renumbered on this basis. Under the lossless condition, the fluctuation range of the first three curvature modal values is small; The fourth and fifth order curvature modal values fluctuate widely. When the damage occurs, the curvature mode values on each mode show a significant decline, and are completely different from the curve under the condition of no damage. Therefore, the arch bridge model can identify the damage, but the identification of the damage location needs further in-depth analysis. The first ten frequencies of the nondestructive states of each operating model are shown in Table 2.

Table 2. The first ten frequencies of the nondestructive states of each operating model

Operating model	Order 1	Order 2	Order 3	Order 4	Order 5	Order 6	Order 7	Order 8	Order 9	Order 10
1	148.121	205.122	514.243	605.215	773.644	0.038	0.075	0.082	0.116	0.286
2	148.644	205.772	515.029	605.430	774.397	0.738	0.821	0.724	1.101	1.255
3	149.060	206.467	515.902	605.661	774.973	0.145	0.111	0.815	0.604	0.687
4	149.357	207.411	516.062	606.528	775.547	0.296	0.623	0.409	1.009	0.975
5	149.695	207.420	516.681	606.776	775.884	0.910	0.194	0.964	0.597	0.650
6	150.111	208.106	517.246	607.480	776.199	0.384	0.972	0.568	0.790	0.471
7	150.971	209.006	518.074	607.912	776.288	0.190	0.349	0.091	0.760	0.366
8	151.653	209.233	518.887	608.262	776.608	0.543	0.221	0.800	0.853	1.216
9	152.384	209.670	518.939	608.961	776.991	0.352	0.216	0.111	0.277	0.662
10	153.318	210.552	519.084	609.083	777.873	0.266	0.339	0.810	0.395	1.166

4. Application of deep convolution network in safety management of geotechnical engineering construction

4.1 Damage Identification Results of Simply Supported Beams

We use the high-level API command Keras stream of Tensorflow in Python deep learning software to build a convolution network that includes convolution layer, pooling layer, noise reduction layer, full connection layer, and predictor layer [11]. The step size is 3, the convolution kernel size is 5 * 5, and the noise reduction layer parameter is set to 0.2. In different input conditions, only the super parameters such as learning rate, maximum training times and training amount of each batch are adjusted. The different analysis of the four input vectors under the network framework is shown below. Based on the finite element model of simply supported beam, the first ten order modal information is extracted. The damage identification results are shown in Table 3.

Table 3. Damage identification results.

Degree of damage	Label value	Actual output value	Error
0.25	0	0	0
0.35	1	1	0
0.55	2	2	0
0.65	3	3	0
0.75	4	4	0
0.25	0	0	0
0.35	1	1	0
0.55	2	2	0
0.65	3	4	1

The predicted value and the actual output value are basically in the same plane. When the damage is large, the recognition accuracy decreases, and only individual data are identified incorrectly. Therefore, through comprehensive analysis, the recognition accuracy of the depth convolution network with natural frequency as the input item is 91%. On the basis of the original natural frequency data and referring to the principle of simply supported beam frequency combination, a part of the training set data set of the simply supported beam frequency combination is given. The predicted value and the actual output value are basically not on the same plane, with large fluctuations. There are many identification errors, and the ratio of individual data error to standard value reaches

2. In the data set of identifying errors, the number of smaller and larger damages is more. According to the synthesis of all output vectors, the recognition accuracy under this working condition is 75%. The subspace analysis method in modal analysis is used to extract the first ten vertical displacements. Considering the small amount of data, the first five curvature is selected as the input item.

4.2 Damage Identification Results of Continuous Beam Bridges

In the selection of finite element model, in order to compare with the RBF neural network in Chapter 2, we first select four different input forms of the same simply supported beam to input into the convolutional neural network. The convolution network model in the linear stacking model is built by using the depth learning software. Its structure is shown in the following figure: first, the data must be preprocessed. Since the network is essentially a multi classification problem, the output items should be labeled first. According to the different degree of damage, it can be divided into 5 categories: 0, 1, 2, 3 and 4. The training data is 125 groups of data, taking 100 groups randomly as the training set, and the remaining 25 groups as the test set. Using keras software, the sequence of establishing sequential linear stack model is: convolution layer 1 - anti overfitting layer 1 - pooling layer 1 - convolution layer 2 - anti overfitting layer 2 - pooling layer 2 - flat layer - output layer. The activation function of the convolution layer uses the relu function, the flat layer does not use the activation function, and the activation function of the output layer uses the softmax classification function in the multi classification. Among them, the mechanism to prevent the over fitting layer is to randomly lose the weight of the specified proportion, which increases the generalization ability of the depth network. In the selection of optimizer, a random gradient descent optimizer is used. When the loss value on the verification set rises for three consecutive cycles, it is considered that it may enter the over fitting, and the training is stopped.

4.3 Arch Bridge Damage Identification Results

Using keras software, the sequence of establishing sequential linear stack model is: convolution layer 1 - anti overfitting layer 1 - pooling layer 1 - convolution layer 2 - anti overfitting layer 2 - pooling layer 2 - flat layer - output layer. The activation function of the convolution layer uses the relu function, the flat layer does not use the activation function, and the activation function of the output layer uses the softmax classification function in the multi classification. Among them, the mechanism to prevent the over fitting layer is to randomly lose the weight of the specified proportion, which increases the generalization ability of the depth network. In the selection of optimizer, a random gradient descent optimizer is used. When the loss value on the verification set rises for 3 consecutive cycles, it is considered that it may enter the over fitting, and the training is stopped. The finite element model of the arch bridge is established based on the natural frequency, and the first ten frequencies are extracted by using the subspace analysis method in the modal analysis of the finite element analysis software. The training data is 85 groups, and the test data is a combination of 68 groups and 17 groups with 75% injury degree, so the test data is 85 groups. The first ten frequencies on the test set are selected here for detailed introduction. When the neural network training is completed, the training results are shown in the Table 4:

Table 4. Training results

Degree of damage	Label value	Actual output value	Error
0.25	0	1	1
0.35	1	1	0
0.55	2	2	0
0.65	3	3	0
0.75	4	4	0
0.25	0	0	0
0.35	1	1	0
0.55	2	2	0
0.65	3	4	1

It can be seen from the above training result table that when the damage degree is less than 65%, there are certain recognition errors, not only when the damage degree is small, the recognition error rate is high. However, when the damage degree is greater than or equal to 65%, the identification accuracy is high. Therefore, it can be judged that the neural network model under this input condition is only suitable for predicting structures with large damage values [12]. Thus, the deep convolution network is an important fitting model for the description civil engineering construction safety.

5. Conclusions

By building the simply supported beam model in the finite element analysis software, we extract the relevant data of its modal analysis as the input of RBF neural network, and propose the step-by-step identification method and the comprehensive identification method. When the structure and vibration mode of the bridge are relatively clear, the neural network with relatively simple, fewer layers and fewer neurons can be selected for information extraction. When the structure and vibration mode of the bridge are complex, the deep neural network with stronger nonlinear information extraction ability should be selected. In the finite element model, the depth convolution network has better information extraction ability and nonlinear fitting ability than the other two neural networks in the field of structural damage identification, so it can do further depth analysis.

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