Optimization of CNN and LSTM Based Application on RC Frame and Long-Span Structural Health Monitoring

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Abstract

As an important field of artificial intelligence, neural network combines computer vision and image processing to extract the surface features, displacement and other parameters of the object to be measured. This paper mainly studies the optimization of CNN and LSTM based application on concrete frame and large-span system in structural health monitoring covered with concrete surface defects and possible damage prediction. The detection techniques including CNN, FCN and LSTM neural networks.

Keywords

Convolution Neural Network, Recurrent Neural Network, Chaos Theory, Frame and Large-span Structural, Structural Health Monitoring

1. Introduction

Based on the physical mechanism of network topology knowledge, artificial neural network is distributed and transmitted through a large number of neurons [1]. Their common characteristics are large-scale parallel processing, distributed storage, elastic topology, high redundancy and nonlinear operation. Therefore, it has high operation speed, strong association ability, strong adaptability, strong fault tolerance and self-organization ability. Since it was first applied to the research field of civil engineering in 1989, neural network has been involved in geotechnical engineering, building construction, traffic engineering and other fields to deal with damage assessment, system identification and optimization, structural control and regression analysis.

2. BP Neural Network

In 1986, Rumelhart and McClelland proposed BP neural network [2]. The characteristic of BP neural network is the correction of error back propagation. For the specific principle, please refer to "combining artificial neural network with principal component analysis and cross validation technology to predict the compressive strength of high performance concrete [3]".

2.1. Application of BP Neural Network in Spatial Lattice Structure Identification

In the existing SHM [4] structural health detection system, the modal parameters of spatial grid structure are greatly affected by the environment. At the same time, the lack of research on local damage and sensor layout makes the health status of the whole grid structure unable to get a good response. Changes in material properties may also result in the inability to establish an objective and applicable evaluation system in monitoring.

2.2. Identification Principle and Development Direction

The identification uses the grid structure finite element analysis method to release the nodes and bending degrees of freedom at both ends of the element member, and only limit the translational degrees of freedom in three directions. The shear wall and floor are simulated by shell element, and the beam and column are simulated by element frame with the help of MATLAB and BP neural network, the nonlinear relationship between finite element displacement and overall structural stability is reflected.

The structural health assessment system is divided into four levels. The first level is structural health assessment. The second system layer is divided into two parts: building structure and elements. The third layer corresponds to the structural position, stress ratio and damage degree in the building components. Then data transmissions to the indicator layer to quantify the function and status of the third layer.

In the component system the weight is related to the 'comprehensive importance' of the elements which represents the consequence of RC components failure and the possibility of damage set as IGi:

$$I\Gamma\iota = PI/P\mu\alpha\xi,\ P\iota = |\sigma i(q)|. \tag{1}$$

Ri refers to the response of the 'i'th element under the most dangerous working condition, Rmax is the maximum value of all elements responses, σi is the stress response of the 'i'th element, and 'q' is the most disadvantage load combination of the elements. Index 'I' greater than 0.7 refers to the 'important components'. When calculating the weight coefficient of the index 'I', the weight method is used that wi is the weight coefficient of the 'i'th component and 'm' is the amount of components.

$$\omega\iota = I\Gamma I / \sum_{i=1}^{m} I\Gamma\iota \tag{2}$$

The structure system includes the establishment of weight coefficient and the structure comprehensive evaluation method based on fuzzy inference theory. The establishment of weight coefficient selects the 9/9～9/1 scale method in Table 1, and the function model f(x,y) is used to determine the importance of index X and Y of the evaluation objective [5].

Table 1

Four Scaling Methods of Analytic Hierarchy Process

The former compares with the latter	1～9	9/9～9/1	10/10～18/2	Index
Equal importance	1	9/9	10/10(1.000)	90(1.000)
Partially importance	3	9/7	12/8(1.500)	91/9(1.000)
Obviously importance	5	9/5	14/6(2.333)	93/9(1.000)
Very importance	7	9/3	16/4(4.000)	96/9(1.000)
Extremely importance	9	9/1	18/2(9.000)	91/9(1.000)

The fuzzy comprehensive evaluation includes the establishment of membership function and the centralized analysis of fuzzy evaluation vector. The function relationship between membership degree R and index value I is presented by trapezoidal and approximate triangular distribution. For the centralized analysis of fuzzy evaluation vector, the fuzzy evaluation vector is

$$IZ = \sum_{i=A}^{D} ci * \mathrm{riz} \tag{3}$$

The health status grade of the structure is obtained from the index grade classification table corresponding to Iz (Table 2).

Table 2

Relationship between Evaluation Grade and Index Value

Serial Number	Classification	Index Range
1	Class A (health)	1.00≤ IZ
2	Class B (sub-health)	0.95≤ IZ <0.95
3	Class C (damaged)	0.90≤ IZ <0.95
4	Grade D (morbid)	IZ <0.90

Using the test set to evaluate the accuracy of neural network, the identification accuracy of BP Neural Network is relatively high, and the minimum classification accuracy error of neural network structure in the test is 4.3%, which is the theoretical basis for realizing accurate evaluation of automatic identification. Through the training of BP Neural Network, the increase number of layers and nodes show great impact on the evaluation accuracy of neural network, the identification accuracy of neural network will be efficiently enhanced with the increase of layers and the number of unit nodes. Further research probably focus on the impact indicator types of existing evaluation models, experimental design models, optimal design of sensors and life prediction of lattice structures.

3. Convolution Neural Network(CNN)

The convolution idea of Convolution Neural Network comes from BP neural network. As a one-dimensional fully connected structure, BP neural network is prone to problems such as local minimum, slow convergence and weak generalization ability. Compared with the method of updating weights through back propagation of BP neural network, CNN adopts a multi- perception structure with local connection between layers and two-dimensional convolution template to share weights to reduce the parameter scale and the probability of over fitting.

The defects of CNN include that when the network layer is too deep, the parameters near the input layer will change slowly by using BP propagation to modify the parameters; The gradient descent algorithm is easy to make the training results converge to the local minimum rather than the global minimum; The pooling layer will lose a lot of valuable information and ignore the correlation between the local and the whole. There are some classic CNN models below.

3.1. AlexNet Migration Learning Network

3.1.1. Overview and Related Previous Research

In the neural network structure, the transfer learning network can reuse the model developed for one task in another target as the starting point, which saves a lot of computing and time resources required for training the neural network *(Fig. 1)*.

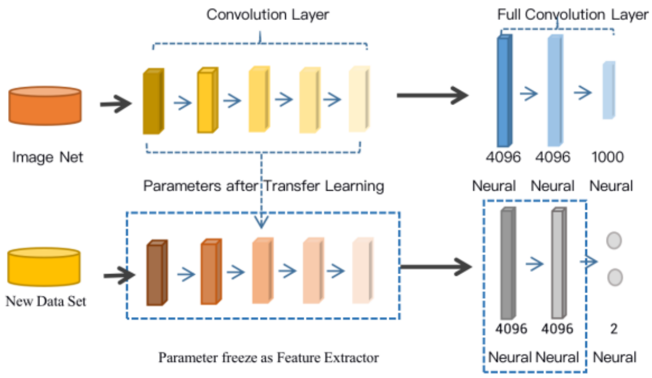

Figure 1: AlexNet Learning Network Computing Principle

The advantage of the AlexNet including calculation acceleration powered by CPU(GTX 580 3GB); the concept of pooled step size is proposed to reduce the error rate; ‘Dropout’ technique is proposed to reduce over-fitting and increased independence between neurons; in view of the oscillation of convergence speed, Alexnet adopts BN normalization method to reduce internal Covariant Shift to a certain extent. However, in the training process of Alexnet, the convolution kernel with large size is used, which has too many parameters and is prone to be over-fitting. Moreover, Alexnet has high requirements for storage and computing time, so it is difficult to deploy it on an appropriate GPU.

3.1.2. Application of AlexNet in RC Frame Structure Identification

The damage identification of reinforced concrete frame structure based on convolution neural network includes the collection of damage data of frame structure, the damage identification based on improved transfer learning network and the visual interface of damage frame structure identification. The alexnet network model is trained by the feature extractor [6], and does not need to be trained many times from top to bottom through a large number of convolution layers. However, it still takes a long time to extract features by pretraining the filter parameters and weights of CNN layer.

Finding sensitive damage index is the key link of identification. The natural frequency can reflect the overall characteristics of the structure and has high test accuracy, but the identification of symmetry problems is weak, which is more suitable to judge whether the structure is damaged. The input parameters of the network are mostly discrete, and stress redistribution occurs near the damage location. The test accuracy and sensitivity of low-order vibration modes and strain modes are relatively high. In the damage feature extraction stage, the structural damage model is established by reducing the elastic modulus of components (Fig. 2), and the natural frequency, vibration mode and strain mode parameters are extracted.

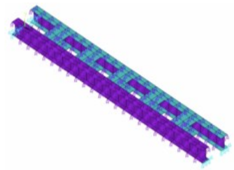

Figure 2: Structural Damage Model

In the process of sample training, the optimal network model will be obtained by adjusting the parameters Batchsize, Epoch and optimizing the function [7]. The parameter Batchsize refers to the number of training samples required in a network for once forward and backward propagation operation. An Epoch refers to a full training cycle on the entire training set. Under a given epoch parameter, increasing the value of Batchsize within a reasonable range could improve the memory utilization and the parallel efficiency of large matrix multiplication. The optimization function includes Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (ADAM). SGD algorithm uses a batch of incomplete data each time to avoid the local optimal solution. The mini batch method is used to mitigate the loss function to fluctuate caused by the parameter update of the high variance in each training sample for obtaining the minimum value of the given loss function. ADAM algorithm could calculate the adaptive learning rate of each parameter. This method not only stores the exponential decay average of the previous square gradient of AdaDelta, but also maintains the exponential decay average of the previous gradient.

AlexNet transfer algorithm has effectively solved the problem of damage identification of frame structure. The further research probably focus on how to design graphical user interface, so that the operator is able to view the machine identification results by simply pictures input, and then evaluate the whole frame damage structure effectively.

3.2. Joint CNN&LSTM

3.2.1. Overview of joint CNN & LSTM

CNN & LSTM regarded as a neural network is able to uniformly extract the spatial and temporal features of bridge signal data [8]. By comparison, CNN has weak damage degree identification ability while LSTM and MLP is vulnerable in position identification ability and damage degree identification ability. CNN & LSTM which can extract the spatial and temporal information of damage signals at the same time, has a good prospect in the application of bridge damage identification.

The selection of loss function, classifier and optimizer of joint CNN & LSTM has a great impact on the actual performance of the network [9]. The loss function is the main index used to measure the error between the prediction and correct result of neural network model. The commonly used loss functions are Cross Entropy, CE and Mean Squared errors, MSE [10]. Cross Entropy is often used to calculate the loss of network output z1 and real label z of classification problems LCE(z,z1):

$$\text{LCE(z1,z)}=-\sum_{m}[zlogz1+(1-z)log(1-z1)] \qquad (4)$$

MSE loss function is often used to calculate the loss of network output z1 and real label z of regression problem LMSE(z,z1):

$$\text{LMSE(z,z1)}=\frac{1}{m}\sum_{m}(z-z1)2 \qquad (5)$$

Classifier is used for mapping the input feature vector to the predicted category label [11]. Compared with SVM, Softmax classifier is the generalization of logic regression model in multi-classification problems and has stronger classification ability.

3.2.2. Application of CNN&LSTM in Bridge damage identification

Problems for solution: The main methods of bridge damage identification contains CNN, RNN, MLP. Present problems to solution including (1)Deep neural network can carry out 'end-to-end' learning, it does not need feature index extraction and directly uses the original data for training. However, the 'end-to-end' learning method performs poorly [12]in bridge damage identification. (2)Because the performance of different neural network models in bridge damage identification is also quite different [13]. Therefore, it is particularly important to establish a depth neural network model suitable for bridge damage identification. (3)When building bridge damage samples, the training sample data extracted from the simplified finite element model is different from the corresponding damage of the actual bridge to a certain extent, that is, the training set and the test set obey different data distribution laws [14] which will inevitably affect the final result of damage identification.

Establishment of bridge damage sample database: The establishment of bridge damage sample database includes the establishment of bridge finite element model, obtaining accelerated response data and establishing damage sample database. The finite element model is designed as the plain jolter model of OPENSEES [15] cable-stayed bridge. In order to more accurately simulate the damage of the bridge under vibration excitation, the data such as the quality of the main beam, the elastic modulus and initial tension of the cable, the stiffness of the support, the elastic modulus and unit weight of the concrete are corrected. The acceleration measuring points are arranged according to the vulnerable position of the structure [16].

The damage analysis data include the instantaneous vibration frequency, average vibration frequency, instantaneous energy, average energy, energy density and combination characteristics of the bridge, which need to be obtained by decomposition and transformation of the acceleration response of the bridge. Compared with EMD, CEEMDAN effectively solves the problem of "mode aliasing" of EMD [17]. CEEMDAN adds adaptive Gaussian white noise in each section, and obtains each modal component IFM by calculating the only residual signal. The obtained IMF signal forms an analytic signal with the original signal s (t) through Hilbert transformation [18], the instantaneous amplitude and instantaneous frequency are obtained through derivation and obtains the establishment of bridge finite element model, obtaining accelerated response data and establishing damage sample database [12].

Damage identification of joint CNN & LSTM: The damage identification of joint CNN & LSTM includes the input, training and testing of joint CNN & LSTM. The physical meaning of the input data of CNN and LSTM is in Table 3.

Table 3
Comparison table of physical meaning of Conv 1D and LSTM input data

Input Data	Neural Network			
	Convolution 1D		LSTM	
1	N	Batch Training Size	seq-len	Dimension of Each Sample
2	C_{in}	Dimension of Each Sample	batch	Batch Training Size
3	L	Number of Individual Samples	input-size	Number of Individual Samples

The training process mainly includes normalizing bridge damage samples with function:

$$x1=\frac{x-x(min)}{x(max)-x(min)} \tag{6}$$

Iterative inputting it into the built CNN & LSTM to get the recognition result of the corresponding position. The error between the predicted damage identification result and the theoretical damage identification result is calculated by Cross Entropy. The appropriate network parameters are obtained by error back propagation and update the whole network. The verification set is used to test the network performance, and a relatively suitable joint CNN & LSTM model for bridge damage identification is obtained.

The test stage of joint CNN & LSTM shows that the damage location and damage degree identification effect of the combined feature sample library is the best, which can better reflect the damage of the finite element model of cable-stayed bridge [12].

The bridge damage identification combined with CNN & LSTM has defects. The damage accuracy of the measured damage sample library is slightly lower than that of the theoretical finite element sample library, which may be caused by model simplification error and measured data error. Future research directions may include obtaining more indicators that can effectively describe bridge damage characteristics based on bridge vibration frequency and energy information, such as GAF(Gramian Angular Fields) and MTF(Markov Transition Fields), and enrich the sample database of different types of bridge damage.

4. Full Convolution Neural Network (FCN)

4.1. Features of Full Convolution Neural Network

FCN extends the end-to-end convolution neural network to semantic segmentation for the first time which is the basis of later neural network structure such as U-Net. The traditional CNN dimension reduction processing method has several disadvantages: the memory overhead is inefficiently large with the repeated adjacent pixel blocks; third, the size of the pixel block limits the size of the sensing area. FCN is capable to accept images of any scale, solves the semantic level image segmentation; converts the full connection layer into the deconvolution layer, recoveries the category of each pixel from the abstract features (Fig.3). FCN neural network also has a skip layer structure, the first few layers highlight more local details of the image, and the last layer contains more information of the original image (Fig.4).

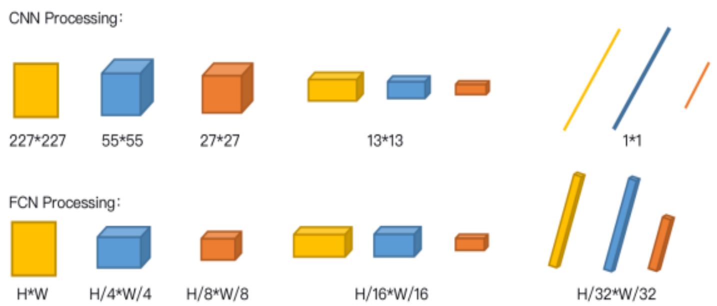

Figure 3: Processing Flow Chart of CNN Neural Network

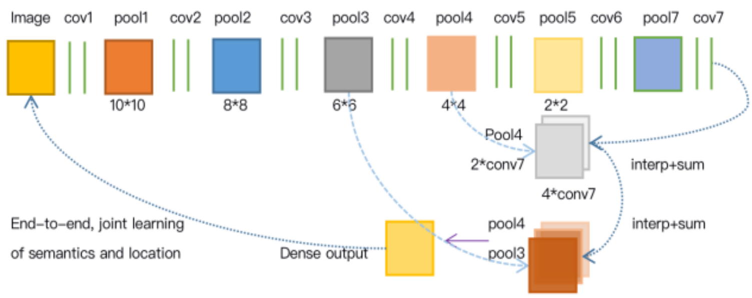

Figure 4: Step Skipping Structure of Full Convolution Neural Network

However, FCN is improved based on CNN, the applicable spatial regulation in the segmentation method based on pixel classification is ignored, which lacks spatial consistency.At present, the research mainly focuses on the use of image processing technology to detect surface cracks and corrosion, for example the successful application of the bridge coating quality evaluation. However, there are relatively few studies on surface defects such as honeycomb, pitted surface, bubble, defect, corner falling, and faulting of slab ends.

4.2. Application of Full Convolution Network in Fracture Identification

4.2.1. Previous Studies and Existing Problems:

The depth learning methods for crack identification can be divided into sliding window algorithm in image input stage and image segmentation method in crack feature extraction stage. In the traditional sliding window algorithm, the use of full connection layer leads to that the input image size is only limited to the design size of sliding window, and the batch recurrent input of a large number of windows is very time-consuming. At this stage, full convolution neural network structure(FCN) is used to transform the full connection layer at the end of CNN into the deconvolution layer to accept input images of any size.

In the stage of cracks feature identification, the threshold calculated by Ostu algorithm is higher than the actual one, resulting in the extracted cracks wider than the actual one. The noises are difficult to be removed by mathematical morphological image processing (open operation and close operation) or judgment of connected isolated noise points. The proportion of narrow and long crack area in the whole image is normally much lower relative to the background. The imbalance of samples will cause the model training processing allocating more attention to the training of negative samples and partly ignoring the positive samples, affect the detection effect.

4.2.2. Improvement Method based on Traditional Neural Network

Threshold Segmentation Method based on Improved Ostu Algorithm: Neural network crack recognition process includes: image acquisition, preprocessing and enhancement technology; image threshold segmentation based on Ostu algorithm, image cleaning and edge thinning processing; filter the output image properties through the classifier, including length, width, area, perimeter, angle etc.

In the image preprocessing stage, M2GLD algorithm (min-max gray level discrimination) is introduced to improve the gray intensity of potential non cracked pixels and reduce the gray intensity of potential cracked pixels. Meanwhile, M2GLD is able to convert the obvious single peak histogram into a more separable bimodal histogram which is helpful to determine the optimal threshold by using Ostu method. After image preprocessing and enhancement, Ostu algorithm is used to solve the image segmentation threshold. Firstly, the overall average value of gray level is calculated: $\mu=\omega 0(t)\mu 0(t)+\omega 1(t)\mu 1(t)$. The threshold top is calculated by using the optimization function:

$$\mu\alpha\xi\ \phi\sigma(\tau)=\omega 0(\tau)(\mu 0(\tau)-\mu)2+\omega 1(\tau)(\mu 1(\tau)-\mu)2 \qquad (7)$$

The formula on the right side of fs(t) represents the Ostu value between the target and the background. However, in the case of single peak histogram and close to single peak histogram, this method probably encounter the difficulty of threshold recognition. The target of the image cleaning stage is to segment the image with pixels less than NP, and judge by the shape of the segment images[19].

The improved Ostu algorithm based on M2GLD can be easily integrated into many crack detection and classification models developed in the future. The limitation of this method is that the user should have to fine-tune two parameters: Adjustment Ratio and Margin Parameter. Therefore, future research directions may include the application of optimization methods to automatically identify the appropriate adjustment ratio and margin parameters.

Crack Feature Extraction Method based on Progressive Cascade Convolution Neural Network: In view of the fact that the characteristics of crack region are not significant compared with the background region in the process of crack identification, the progressive cascade convolution neural network is proposed for concrete surface crack identification. The method contains two stages. In the first stage, a full convolution neural network is designed. The sliding window algorithm is used to intensively scan the image, exclude most of the non crack regions, and take the windows which containing cracks as the region of interest. In the second stage, a lightweight U-net image segmentation network is designed to extract cracks from the region of interest which output in the first stage.

In the first stage, each image is intensively scanned and segmented by setting the pixels and steps of the training sample and test sample. In the image scanning process, compared with the convolution neural network calculation of multiple sliding window images alone, the full convolution neural network can input images of any size, which reduces the repetitive calculation of many windows overlapping parts. The output probability P of the classification model is judged according to the threshold TP, and the recommended value is 0.9 ~ 0.999:

$$\mathrm{f(x)} = \begin{cases} 0, & P \le T_P \\ 1, & P > T_P \end{cases} \tag{8}$$

In the second stage, U-net uses the coding idea and jump layer connection to superimpose and fuse the same scale feature images of the network shallow encoder and deep decoder, so as to make the image segmentation effect more fine and accurate. U-net only extracts the region of interest with obvious cracks. In view of the narrow and long crack characteristics, which are more sensitive to the loss of information, the structural design replaces the pool layer operation by adjusting the step size; Aiming at the characteristics that image cracks mainly contain edge texture properties, and there are not many high-level semantic features compared with some complex feature objects, a lightweight U-net neural network is used to improve the computational efficiency.

This method can improve the performance of concrete crack identification. For the progressive cascade convolution structure, the next research focus is probably to explore that if only constructing one full convolution neural network can complete the screening of crack regions of interest and the segmentation of cracks in the regions of interest at the meantime.

4.3. Application of Full Convolution Neural Network in Steel Corrosion Identification

4.3.1. Previous Studies and Existing Problems:

Identification of reinforcement corrosion degree based on neural network was first proposed by long j et al. Whom in the research attempted to put forward the convolution network neural structure. Lee et al. Developed an automatic processor that can identify the corrosion defects of bridge coating [10], Son et al. Used J48 decision tree algorithm to quickly and accurately determine the corrosion area [9]; Shen et al. Proposed a identification method of reinforcement corrosion strength based on artificial neural network [4]. Garcia Garcia et al. Analyzed and summarized the common semantic segmentation network structures so far, and introduced the more successful segmentation networks such as Segnet, Deeplab, Crfasrnn, etc. [12].

With the detection of traditional image processing and identification technology, steel corrosion is easily affected by noise such as illumination and shadow and the combination of several different surface defects in surface color identification.

4.3.2. Identification Principle

Steel corrosion identification also has high requirements for image color identification, including the treatment of the effects of lighting, shadow and the combination of several different surface defects in the real environment. In the preprocessing stage, the image is converted from RGB color gamut to YCbCr color gamut. In feature extraction process, the first layer of the hidden layer is set as the convolution layer, and the input image is convoluted and symmetrically filled with the image edge, in order to ensure that the image edge is included in the convolution process and avoid the premature loss of the information at the image edge. Aiming at the defects that the various size of the feature images after convolution operation, the L2 regularization function [4] is applied to batch processing of the image, and then the Rectified Linear Unit(Relu) is used to the function activation.

The improvement based on deep learning neural network is mainly to preprocess the image in the early stage, including image denoising by using median filtering method, edge detection method based on wavelet decomposition and image feature location method based on genetic algorithm. The training accuracy reaches up to 91%, and the testing accuracy can also reach 85% through this methods. When the algorithm is applied to the identification of plain carbon steel corrosion images, the identification training accuracy and testing accuracy could reach more than 94% [4]. However, it usually takes more than three years to generate a stable rust layer under actual environmental conditions. Due to time reasons, the sample richness of reinforcement corrosion image sets is insufficient, and the accuracy of reinforcement corrosion identification results is affected.

5. Recurrent Neural Network in Deflections Prediction

5.1. Application of LSTM Network in Deflections Prediction

Long short-term memory (LSTM) is a special kind of RNN, which is used to predict the future deflection values and reflects the changing trend of bridge structures. Compared with RNN with only one transmission state, LSTM has two transmission states: cell state and hidden state. It solves the problems of the gradient exploration and vanishing gradient descent problem in traditional RNN.

5.1.1. Identification Principle

The LSTM networks includes three layers, input layer, LSTM layer and regression layer respectively. X represents the extracted features worked as input data samples while Y indicates the deflection data as the output data trained by back-propagation with gradient descent.

The hidden unit called memory cell as the core of LSTM neural network to memorize the information of long-term input samples[9]. It includes three phases, 'Forgot Gate' is mainly used to selectively forget the input from the previous node, control the ct-1 of the previous state through the calculated z f, and determine the information to be retained. 'Input Gate' is mainly used to selectively memorize the input data x t, the current input is represented as z, the selected gating signal is controlled by z i. Add the results obtained in the above two steps to transfer to the next state c t. 'Output Gate' controlled by z o determines current output data and scaling data co from the previous stage through activation function 'tanh' (Fig.5).

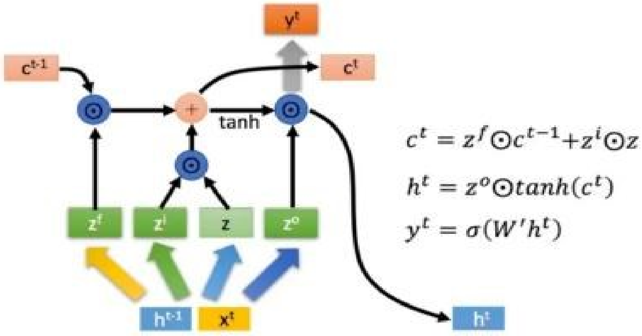

Figure 5: Activation Function 'tanh'

5.1.2. Bridge Structure Deflections Prediction based on LSTM Network

In bridge structure, the characteristics of grider deflection is selected as the reference reflecting the bridge health condition. The deflection can timely reflect the bridge structure condition under the moving load and external environment, according to which, it has strong robustness to noise and sensitiveness to structure damage.

The input references including the temperature, crack, humidity, strain and deflection. A 3-layer LSTM model is trained with the total number of input and output vectors which is more than 8000, while the dimension of cells state and hidden state is set to be 512. The time step, batch size, learning rate is setting as 3, 128, 0.00044, respectively, to balance the performance and training time. In the output stage, in order to minimize the mean square error (MSE), back propagation with gradient descent is used to train the weight metrics. The calculation of MSE as follow:

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}(yi-Yi)2 \tag{9}$$

At the best predictive point, the proportion of error data is less than 1%, and 74% of the data in worst-performing points meet this accuracy requirement[9]. Therefore, LSTM is available in deflections prediction in bridge health monitoring.

6. Existing Problems and Research Prospects

Neural network has the following problems in civil engineering research: (1) the generalization ability of neural network to identify building surface defect samples and structural deflection is weak. (2) the calculation of curvature mode and strain mode is basically based on the assumption of elastic deformation, which has limitations. (3) Neural network structure is difficult to identify building surface defects and structural damage at the same time and establish the mapping relationship between them, because too many parameters are easy to lead to over fitting. (4) RNN and LSTM recurrent neural networks lack the research model of multivariable time series prediction in chaotic system. It is necessary to strengthen the combined application of fuzzy theory and neural network in chaotic structure analysis and prediction.

7. Conclusions

This paper studies the optimization CNN and LSTM based application on health monitoring of frames and long-span systems. Alexnet model is introduced through BP neural network, and the damage identification accuracy of RC frame structure is improved in combination with SGD and Adam algorithm. R-cnn and CNN & LSTM are used for bridge and road disease and structural damage identification respectively. M2GLD and Ostu algorithm are combined with progressive cascade convolutional neural network to detect building surface defects. In the future, neural network can combine fuzzy and chaos theory to identify three-dimensional space model, establish the stress-strain relationship between surface defects and structural damage degree, and establish time series damage prediction through time recursive neural network.

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