Computer Fraud and Security

ISSN (online): 1873-7056

Neural Network Optimization Algorithm for Concrete Crack Image Recognition

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Abstract: Concrete structure is one of the most common materials in modern architecture and infrastructure construction. However, cracks will inevitably appear in the use of concrete structures, which is an important factor affecting the safety and service life of structures. Traditional crack analysis relies on manual participation, which reduces work efficiency and also has human influence. Based on the development of artificial intelligence, image recognition with neural network has become a desirable solution. In order to solve the problem of concrete crack image recognition, an optimization scheme using neural network is proposed. By introducing advanced neural network model and combining with image processing technology, the algorithm realizes the automatic recognition and classification of concrete cracks. In the process of algorithm design, the structure of neural network is optimized, including the network structure, overfitting and the selection of additional modules, so as to improve the recognition and classification accuracy. In addition, aiming at the imbalance of data sets in practical applications, data enhancement technology is introduced to effectively improve the generalization ability of the model. The experimental results show that the proposed neural network optimization algorithm has achieved remarkable performance improvement in the task of concrete crack image recognition.

Key words: concrete crack; Image recognition; Neural network optimization

INTRODUCTION

As one of the most important building materials in the field of modern civil engineering, concrete has been widely used in the construction of buildings, roads, Bridges, tunnels, roadbed slopes, retaining walls and other infrastructure[1]. Buildings made of concrete may have diseases of different damage degrees during use, and cracks, as a typical disease of concrete, are mainly caused by the following aspects in addition to extreme natural disasters[2]: First, cracks are generated due to uneven stress distribution caused by long-term heavy load; Secondly, it is affected by temperature change, such as the deformation of concrete structure in the sun and rain and snow weather, and the long-term erosion of air and rain causes its structure to be corroded, resulting in the weakening of carrying capacity and easy to crack[3]; In addition, the equipment and construction technology of the construction site are also directly related to the quality and life of the building. However, the existing neural network models still have some shortcomings when processing concrete crack images, such as limited feature extraction ability[4] and insufficient model generalization ability[5].

Yann LeCun[6] proposed Le Net model, one of the earliest convolutional neural networks (CNN) in the field of deep learning, in 1994, and successfully applied it to the recognition and classification of handwritten characters in the Bank of America. Its advantage is that it does not require engineers to manually design feature extractors (image data sets for specific recognition objects). Instead, it simulates the brain's visual processing mechanism. Through the feature extraction of data information layer by layer, and the feature fusion from the bottom to the top layer, this method successfully solves the problem of relying on manual design feature extractors in traditional technologies. Realize the recognition and classification of simulated human brain. In this paper, a supervised convolutional neural network was trained by taking road crack pictures taken on the spot by smart phones. The recognition results are compared with the existing hand-extracted features, and it is verified that the convolutional neural network has better image recognition performance. In 2017, Tong et al.,[7] adopted convolutional neural network to recognize asphalt pavement cracks, expanded its function to realize the extraction of crack length, and converted color images (including red, green and blue channels) in the original image dataset into gray images, achieving 94.36% recognition and classification accuracy on the self-made dataset. In the same year, Cha Y[8] proposed a CNN model, which applied sliding window technology to the network model, so that the model could train and test any crack image larger than the original fixed size by sliding window, improve the adaptability of the convolutional neural network, and achieve 98% recognition and classification accuracy on the self-made data set. The pre-processing method of bilateral filtering is used to smooth the image containing cracks, while the segmentation technology is used to identify cracks. This method can greatly reduce the number of noisy pixels and improve the recognition accuracy of cracks. But hardware costs and training costs are relatively high[9].

At present, domestic and foreign scholars have made some achievements in the field of concrete crack image recognition[10], but the existing algorithms still have shortcomings in accuracy[14], real-time[15] and robustness[16]. Therefore, to solve these problems, it is of practical significance to study the neural network optimization algorithm for concrete crack image recognition[14]. Based on this, this study proposes an optimization algorithm based on neural network by analyzing the characteristics of concrete crack image, which provides theoretical support for the application of neural network in the field of concrete crack image recognition.

OVERVIEW OF CONVOLUTIONAL NEURAL NETWORKS

Convolutional neural network and training process

Convolutional computational Neural Networks (CNN) were originally invented by Dr. Le Cun of Toronto

College when Le Cun provided the classic convolutional neural network LeNet5 and used digital handwriting recognition. Convolutional computing neural networks are often used as classifiers and are often used in image recognition techniques. As described in the first part of Chapter 2, the classic model in learning, the CNN (Convolutional Neural Network), in general, consists of five hierarchies: the entry level, the convolutional stage, the aggregation link, the fully connected ladder, and the entry/exit level. This model has significant advantages for image recognition. Once it takes a photo as its input data and goes through a series of convolution and aggregation steps, it generates some high-level or esoteric information elements that represent the content of the photo. The complexity of these messages increases with each level, but their high-level nature is rather difficult to understand. The end result is a one-dimensional vector containing all the relevant content, which is the identifier of the category to which this particular photograph belongs. The whole process, from the acquisition of the original image data to the final confirmation of the ownership label, is based on this technology. Traditional segmentation involves performing specific functions under human-designed rules to obtain the desired data set and then using specialized machines to determine which class each sample belongs to or which attribute value is more appropriate for labeling an object instance. Therefore, we can also think that if we compare the functions of each component of cnn to the above two conventional technical means, we can draw the following conclusions: First of all, it's a part of the entrance passageway, the convolutional passages that are used to capture key visual signals and then it uses the place where it's all joined together called the "full connection" to further process those captured objects to form a complete picture and then it uses another place called the "output. layer" position to give the appropriate answer to achieve the purpose.

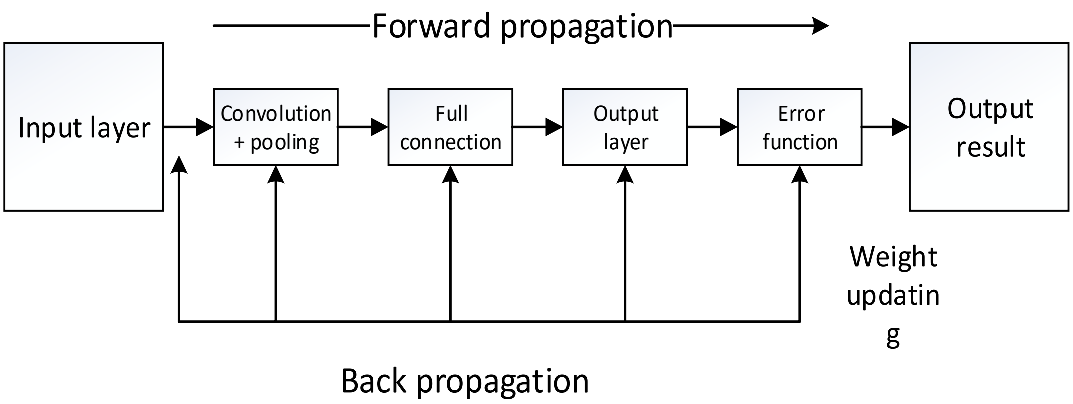


Figure 1 Basic structure of a classic CNN

After the image is entered into the CNN, it will first enter an input layer whose size is equal to the original image size.

TensorFlow deep learning Framework

With the development of deep learning algorithms in various fields, many open source frameworks[19] for deep learning have emerged, such as Caffe, PaddlePaddle, TensorFlow, PyTorch, etc., whose function is to transfer huge data sets of features to be extracted into neural networks for calculation and analysis. TensorFlow is an open source machine learning platform from Google that supports a wide range of deep learning algorithms well, with a comprehensive and flexible ecosystem of tools, libraries, and community resources. In this paper, TensorFlow will be used as the deep learning framework, and the model will be built and trained with the Python language supported by TensorFlow, and the Visual Studio Code compiler will be used.

The name TensorFlow points to two key concepts - "Tensor" and "Flow". The former stands for tensors, which are data structures in TensorFlow and can be thought of as equivalent to the concept of multidimensional arrays. TensorFlow is a system that represents calculations in the form of a graph, where the "Tensor" is represented by a line, and the input and output of various calculations or data are represented by nodes. The various tensors that Flow through the graph are called "flows". TensorFlow has many advantages, including strong readability, smoother running on multi-GPU systems, relatively high code efficiency, and its community development is good, good visualization (including various network topology and performance visualizations, etc.).

IMAGE DATA ACQUISITION AND PROCESSING

Image data acquisition

How to Obtain Data

Considering the accuracy and diversity of the sample set, this paper adopts the following three methods to collect image data samples:

(1) Network search

This part of data is retrieved by various search engines. Images of concrete cracking caused by steel corrosion, other concrete cracks and complete concrete pictures are obtained by searching keywords, and then manually screened to remove pictures with fuzzy quality and unclear images[20]. Since there is no official database related to concrete cracks in the academic circle, there are few data for reference, so the picture data obtained from the network search only accounts for a small part of the data set.

(2) Self-shooting

This part of data is taken by camera in the campus and surrounding construction sites, taking into full consideration the shooting Angle, lighting, shooting distance and other issues, and data collection is carried out in accordance with the image acquisition standards. In this paper, a large number of photos of other causes of concrete cracks and complete concrete photos are obtained by self-shooting.

(3) Corrosion test

Since it is difficult to obtain the picture data of concrete cracks caused by steel bar rust by other means[21], I plan to make reinforced concrete samples by myself, and then conduct accelerated corrosion test of steel bars to cause concrete cracks, and then photograph them. These images form a major component of the data set on cracks caused by steel corrosion.

Image acquisition specifications

To this end, standard image data shooting standards and image acquisition standards are established to highlight the features of image data.

(1) Shooting Angle

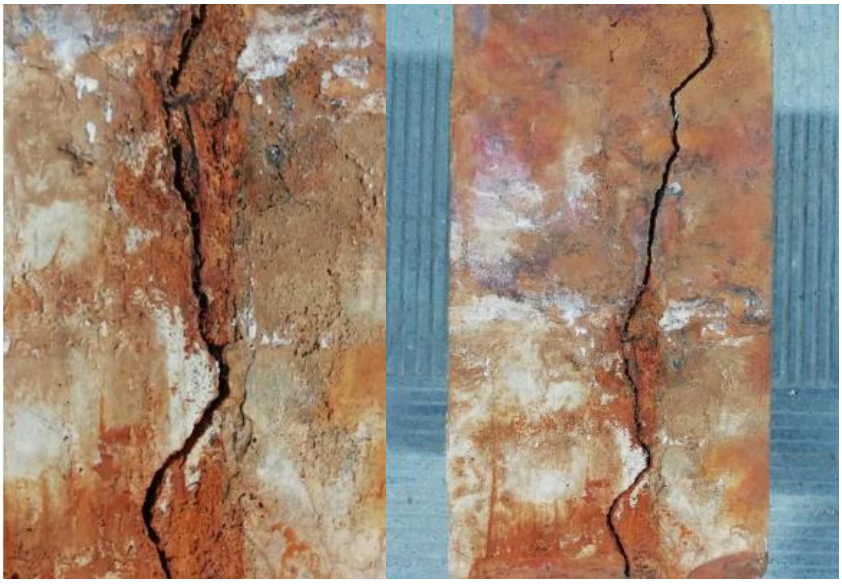
In this paper, because the camera shooting Angle is perpendicular to the concrete surface, there is no geometric deformation, so all the image data characteristics obtained under the same shooting conditions.

a) The camera shoots at an Angle b) the camera shoots vertically

Figure 2. Shooting Angle specification of concrete pictures

(2) Shooting distance

The shooting distance is also an important factor affecting the image quality, and the distance determines the visual field of the image. In the actual shooting, in order to clearly show the crack characteristics in the image, the shooting distance of 20cm was adopted in this paper. As shown in Figure 3.



a) Shoot with the camera 10cm away from the concrete surface b) Shoot with the camera 20cm away from the concrete surface

Figure 3. Specification of shooting distance of concrete pictures

(3) Auxiliary lighting

Light will have a great impact on image characteristics. Under natural light, the background of the image will change greatly, resulting in non-uniform background brightness. Therefore, a uniform auxiliary light will be added in this paper to reduce the background change of the image. As shown in Figure 4.

a) The camera shoots in natural light b) the camera shoots in natural light and auxiliary light sources

Figure. 4 Lighting standards for concrete picture shooting

Image Processing

Image graying

The first step of digital image processing is to process the image gray-scale, in order to improve the computing speed of the computer and extract effective information. In the concrete bending test, the photos taken by the digital camera are all in color. To use the computer for the next step, these color images need to be converted into grayscale images.

The images obtained after image stabilization are all color, so the amount of computation should be reduced as much as possible to improve the real-time performance during image processing. Therefore, the grayscale of the image is a very important link. In the color image, the pixels are composed of red, green and blue, and the gray image, as a unique image representation, also contains all the important information of the entire image. In this paper, weighted average method is chosen to achieve image grayscale, that is, the three components of the image are weighted and averaged according to a certain weight. The conversion formula is given below.

$$\mathrm{Gray}(i,j) = 0.299 * R(i,j) + 0.578 * G(i,j) + 0.114 * B(i,j) \quad (1)$$

Image filtering

Due to the influence of various interference factors, its generation and propagation will be disturbed, which will affect the observability of the image. In addition, after the grayscale transformation of the image, there will be burrs and speckles and other phenomena. To improve the image, it must be filtered. After many experiments, the filtering method based on mathematical statistics is selected at last. Because of its parallel mathematical morphology structure, the image processing speed is greatly reduced.

Using OpenCV for data enhancement

Random tailoring

After determining the size of the picture, you only need to determine the starting point of the crop. OpenCV uses the random.uniform function to determine the position of the starting point at random, and then adds the required number of pixels to the right and up respectively at the starting point, so as to obtain the clipped image.

In this paper, the pictures of 400×1 000 concrete cracks are randomly cropped into 7 pictures of 300×300.

Rotation

Image rotation processing is a common means to increase the amount of data, and rotation does not change the content of the image, does not affect the model's recognition results of the data, and the model trained in this way can recognize pictures from different shooting angles, improve the model's fault tolerance. OpenCV constructs a rotation matrix through the cv2.getRotationMatrix2D function, and then passes the input image through this rotation matrix to get the output image.

However, it is found that some places of these generated pictures are filled with black because there is no concrete. Such pictures can not be used, and the types of the original pictures are too different. After later learning, it was found that these black edges could be cropped out, and the newly generated images were more suitable for training and testing. The principle is to solve the inner rectangle after a rectangle is rotated and its aspect ratio is the same, find the inner proportion and then cut.

The final data set of this paper contains 39,000 concrete photos, among which the cracks caused by steel corrosion, cracks caused by other reasons and intact concrete account for 13000 photos each.

By randomly clipping, rotating and changing the saturation and brightness of the picture, the data volume is expanded. One original crack picture is randomly cropped into two smaller crack pictures; Then the rotation operation of four different rotation angles is performed, and the original drawing is added to get 2× (4+1) =10 crack pictures; Finally, each image underwent two random color transformations to get 10× (2+1) =30 crack data. In other words, 30 effective crack data pictures can be obtained from a shot of raw data through OpenCV data enhancement, and the data set required in this paper can be obtained by eliminating some noise pictures with insufficient crack proportion and insufficient brightness, and by unified size and renaming processing.

RESEARCH ON OPTIMIZATION OF CRACK IDENTIFICATION AND CLASSIFICATION ACCURACY BASED ON NEURAL NETWORK

Basic algorithm model of crack image classification

A complete classification model based on convolutional neural network (CNN) mainly includes image data information input layer, feature acquisition layer, output classification results, etc. When the convolutional neural network is used for recognition and classification task training, the data input layer includes the data image and the corresponding crack classification label, and then a loss function is used to calculate the output result and the corresponding manually marked label, and the difference between the two is calculated. Then the gradient is transmitted Back and the related weights are updated through the way of Back Propagation. The training purpose of the model is to find the optimal solution of a set of parameters that minimize the loss. After the model training is completed, the input data will be obtained by the classification model and the final output result will be obtained. Then parameters will be saved in a certain format.

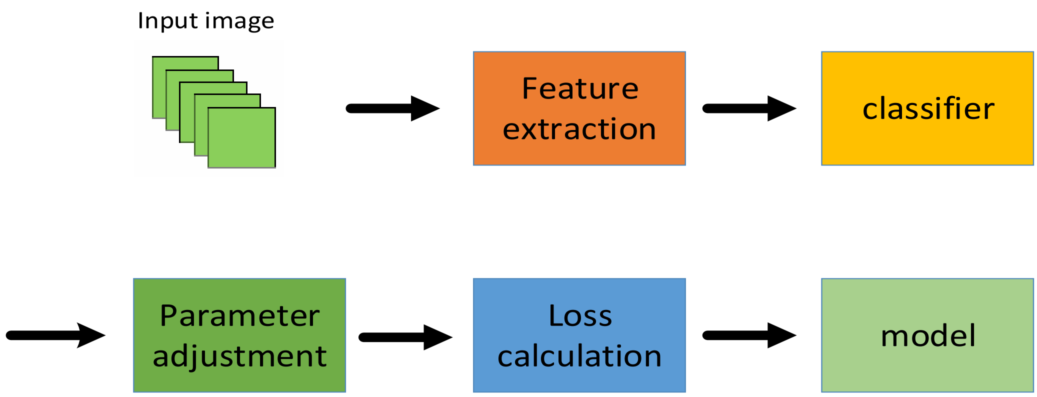


Figure. 5 Process of recognition and classification of concrete cracks based on convolutional neural network

Research on optimization methods of recognition and classification accuracy

Network structure optimization

The structure of convolutional neural network model directly affects the recognition and classification accuracy. When the results of convolutional neural network model classification are not good, the optimization of network model structure is considered first, which mainly affects the feature extraction of training data set. Among them, the dominant operation is the convolution and pooling operation for the analysis of target characteristics. Therefore, the direction of optimization adjustment can be considered in terms of the number and scale of layers of the convolutional neural network and the composition of neurons in each layer (number and size of convolutional nuclei, etc.).

Based on AlexNet convolutional neural network model, Net_1, Net_2 and Net_3 convolutional neural network models are designed, as shown in Table 1, to verify the influence of network structure modification on the accuracy of concrete crack identification and classification.

Table 1 AlexNet and its modified model parameters

Network model	Alexnet	Net_1	Net_2	Net_3
Convolution layer 1	11*11,96,4	11*11,256,4	3*3,96,4 3*3,96,1	3*3,96,4 3*3,96,1
Pooling layer 1	3*3,2			
Convolution layer 2	5*5,256,1	5*5,384,1	5*5,1	3*3,256,1 3*3,256,1

Pooling layer 2		3*3,2		
Convolution layer 3	3*3,384,1	3*3,512,1	3*3,384,1	3*3,384,1
Convolution layer 4	3*3,384,1	3*3,515,1	3*3,384,1	3*3,384,1
Convolution layer 5	3*3,256,1	3*3,384,1	3*3,256,1	3*3,256,1
Pooling layer 6		3*3,2		
Convolution layer 6	6*6,256,1	6*6,384,1	6*6,256,1	6*6,256,1
Fully connected layer 7	4096	4096	4096	4096
Fully connected layer 8	4096	4096	4096	4096
Output layer		2		

(1) Net_1 network model

When a convolutional neural network obtains features in training image data, it mainly does so through Convolution operations. Therefore, on the basis of AlexNet, the Net_1 network model increases the number of convolutional kernels of convolution layer 1- convolution layer 6. The increased number is shown in Net_1 in Table 1.

(2) Net_2 network model

Convolution layer 1 and convolution layer 2 in AlexNet network use large convolution kernels of 11*11 and 5*5 respectively, and large convolution kernels can bring larger local receptive field to the model. However, it brings new problems. Large size means that the training parameters required by the neural network model become more and more. Undoubtedly, this will bring greater computational pressure to the computer equipment, which is not conducive to the training speed of the network to a certain extent. Therefore, it is not only necessary to adjust the convolutional neural network by optimizing the Net_1 network model, but also to adjust the size of the convolutional kernel.

(3) Net_3 network model

On the basis of Net_2 network model, Net_3 network replaces convolutional kernel 5*5 in convolutional layer 2 with 3*3 convolutional kernel. So far, all large convolutional kernel 7*7 and 5*5 in AlexNet network model are replaced with small convolutional kernel 3*3, and the convolutional operation process in the original network model is still realized after replacement. The network model after replacement is shown in Table 1, Net_3.

Overfitting optimization

The main problem of overfitting is determined by data sets and models. From the perspective of data sets, in the process of training data features in machine learning and deep learning, it is mainly to find the one-to-one mapping relationship between the data information in the training set and the corresponding labels, specifically by minimizing the corresponding loss function. In other words, it is hoped that the general data information rules organized and summarized by the neural network model in the training set can be applied to other unknown data, but there is a latent premise here that the distribution of task objectives in the training data set is consistent with the distribution of the general data set in the real world. But in fact, the number of task objectives in the real world is huge, and the commonly used training set is often limited to a small part of it, and may contain useless noise or even interference noise, which will bring adverse effects to model training to a certain extent. Therefore, if the training data set happens to contain a noise with strong interference ability, and it is enough to affect the real distribution of the training data set, the network is likely to treat the strong interference as a common significant feature of the data, resulting in overfitting problems. So the richness of the data set can even determine the upper limit of the model. From the perspective of the model, generally speaking, the more complex the model is, the better the performance of extracting data features, the easier it is to integrate the data, resulting in the integration of noise with strong interference ability. Therefore, when overfitting occurs in convolutional neural networks, the impact can be reduced from the perspective of optimization algorithms, rather than simply adjusting the network size. Reducing the model size may directly lead to the degradation of model performance.

In view of the above problems, Regularization, as a method to improve artificial neural network based on regression, can alleviate the influence of this problem to a certain extent. The regularization method can reduce the test error of the data set and reduce the degree of overfitting, specifically by attaching a regularization term (also known as a penalty term) to the loss function, which can be expressed by equation (2).

$$J = J_0 + \frac{\lambda}{2n}\sum_{w} w^2 \quad (2)$$

In the formula, J_0 represents the initial loss function, and the latter term represents the regularization function, which divides the sum of squares of all weights by the amount of training data n, λ as the regularization coefficient, which is used to adjust the weight relationship between the regular term and the initial loss function. The coefficient estimate can be adjusted in the direction of 0, and the adjustment can be smaller. To simplify the subsequent derivative calculation steps, the regularization coefficient is usually multiplied by 1/2.

In this paper, based on the reference model AlexNet, the above L2 regularization method is applied to the convolution layer of the reference network model to form the Net_4 network model. By training the benchmark model AlexNet and Net_4 neural network models with EPOchs of 50, the results of recognition and classification accuracy on the test set are shown in Figure 6. It can be seen from the figure that after L2 regularization, the recognition and classification accuracy of the Net_4 network model on the test set is improved compared with AlexNet.

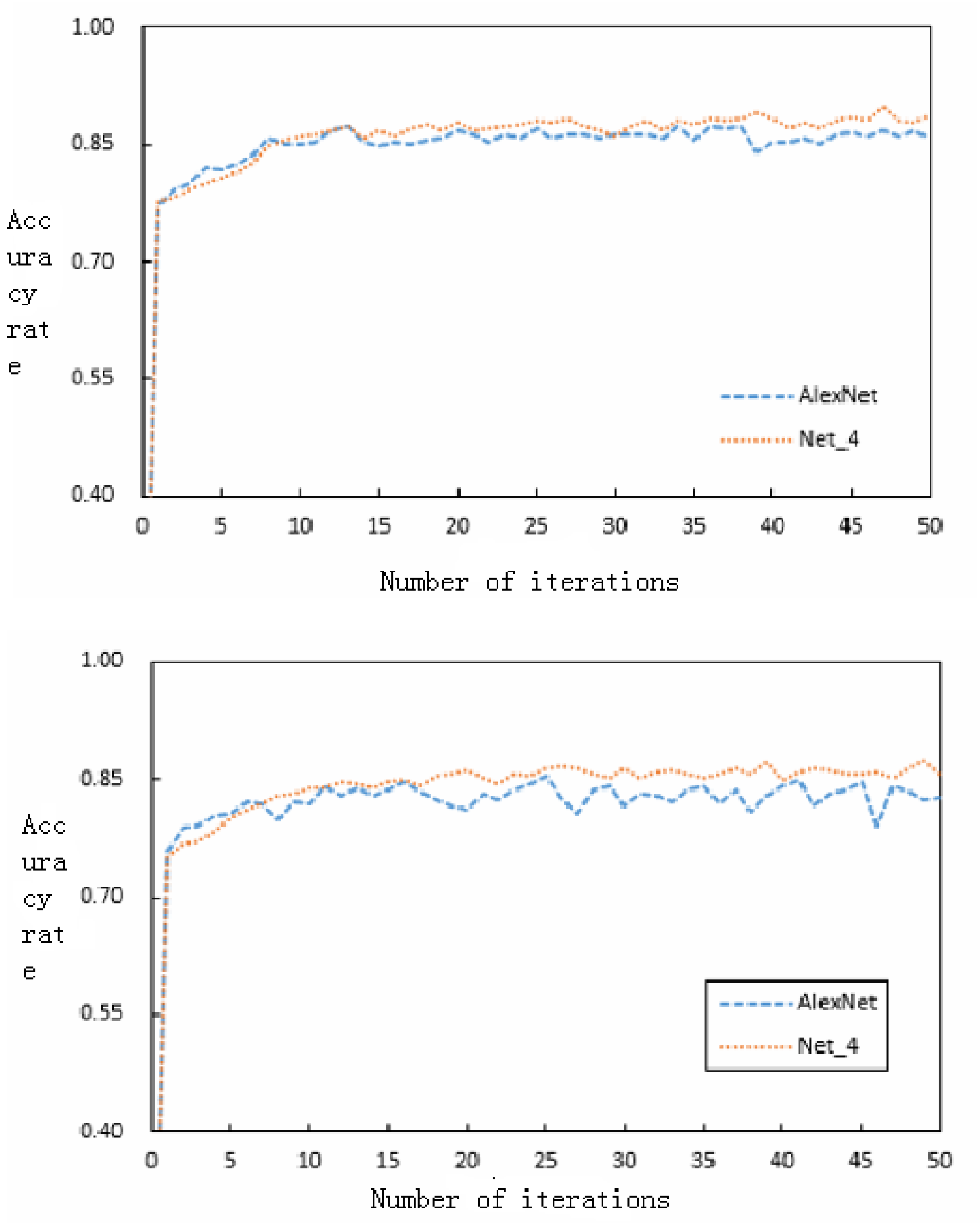


Figure. 6 Experimental results of AlexNet and Net_4 models (from top to bottom are beam cracks and pavement cracks)

Introducing Additional Modules

The channel attention mechanism can suppress unimportant channels and pay more attention to important channels. Therefore, different weight parameters can be assigned to each channel according to its importance. Meanwhile, the convolution operation used in feature extraction involves changing the number of channels and transforming the dimensions of channels. Therefore, the channel attention mechanism can achieve the effect of extracting target features more accurately.

Not all regions in an image are useful for detection tasks, and some regions are invalid feature information. The spatial attention mechanism can generate a spatial attention map from the convolution feature map, which is calculated by the Sigmoid function. The attention map is essentially a weight map in spatial dimension. It processes the spatial position of the feature map, suppressing the unimportant information while focusing on the important position information. The model obtains spatial attention by multiplying the feature map points in the process of attention map and feature extraction. Through the end-to-end learning process, the spatial attention map can automatically re-plan the feature map and divide the corresponding weights, so as to highlight the important features in the feature map and suppress the useless features in the feature map. The essence of this mechanism is to redistribute information resources, and the criterion of allocation is obtained through corresponding learning. It changes the previous situation of equal allocation to different resources and focuses on the importance of different information. This mechanism can recognize different data sets according to different tasks and make the model focus on the feature points according to the importance. Among them, Spatial Transformer Networks (STNet) is one of the representative spatial attention models.

The channel attention mechanism distinguishes the feature information between channels by giving different weight parameter values, and the spatial attention mechanism distinguishes the information at different positions in the feature map by giving different weights according to their importance, and a new module convolutional attention mechanism module (CBAM) is obtained after combination. The specific operation mode of this module is shown in FIG. 7. First, the channel attention module performs the operation of pooling (maximum pooling and average pooling) of the convolution feature map obtained by the channel attention module, and then performs the convolution operation through the two-layer artificial network to obtain a new feature map by convolution, and then processes the new feature map by nonlinear function to obtain a weight parameter Mc. By combining it with the original feature map F, a new feature map F' can be obtained. After the weighted result is obtained, the feature map of the final processing is obtained through the spatial attention module. The spatial attention module pools the newly obtained feature maps F', combines the results of their operations, and then Convolution operations are carried out and the weight coefficient Ms is obtained through nonlinear transformation of Sigmoid function. Then the new feature map F' is obtained by multiplication with feature F'.

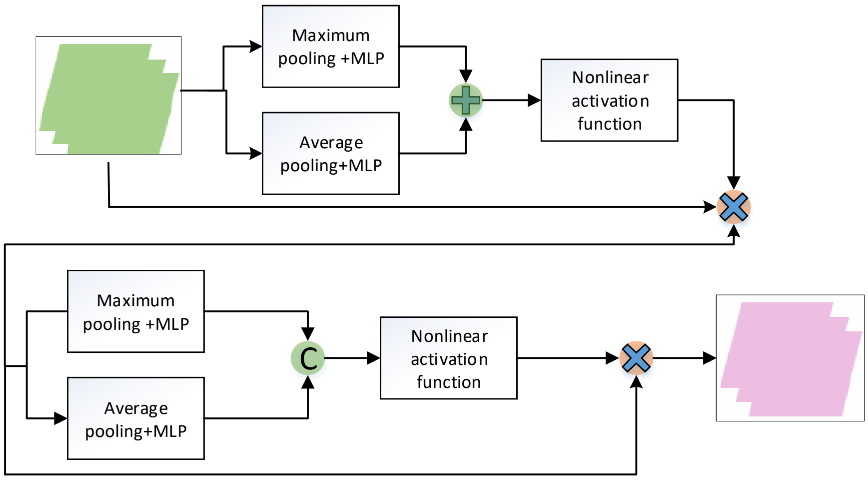


Figure 7 Overall CBAM framework

Model to improve the classification accuracy of concrete cracks

Combined with the research and improvement methods for improving the classification accuracy of concrete cracks in the previous chapters of this chapter, the network model finally designed in this paper is based on the deep learning framework TensorFlow2.0, which improves the benchmark network model accordingly. These include modifying network structure parameters, adding regularization operations, and introducing additional modules (Attention mechanism module CBAM). The convolutional neural network model architecture Um_Net proposed in this paper is shown in Figure 8.

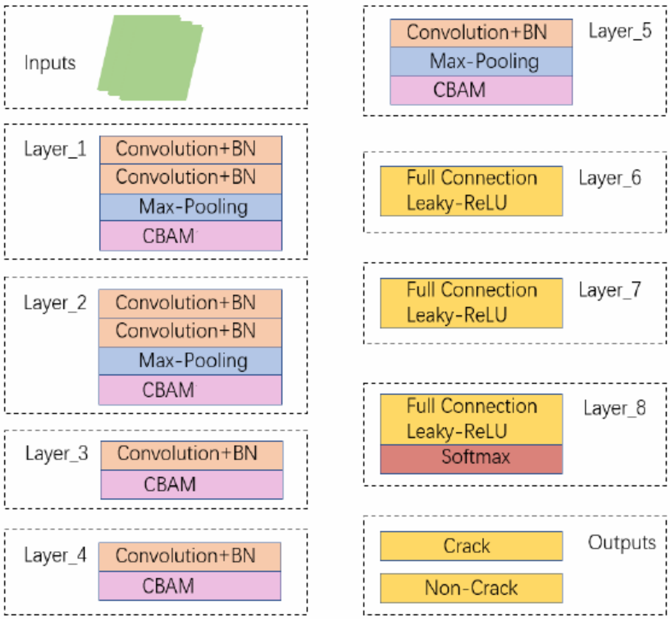


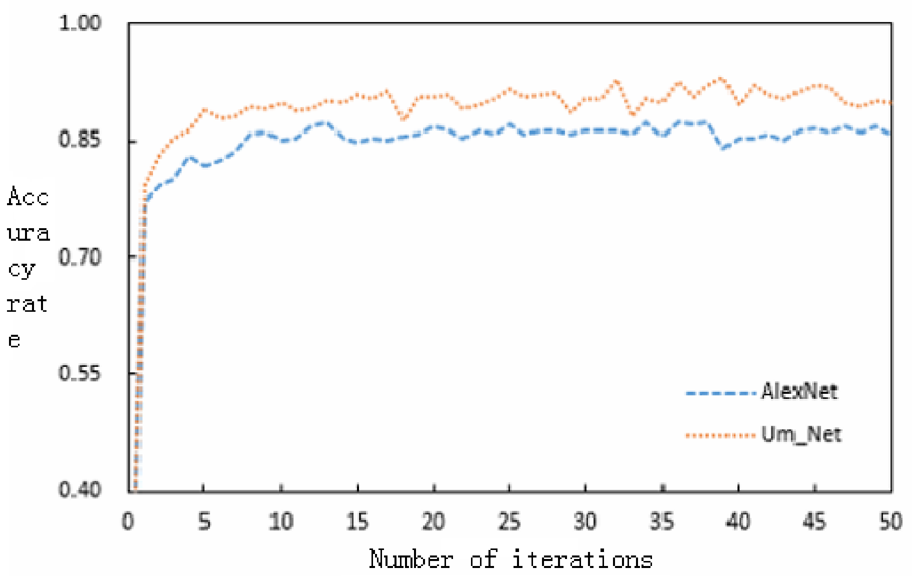
Figure. 8 Improved convolutional neural network model Um_Net

Precision comparison experiment and analysis

Compared with the benchmark model AlexNet and the improved convolutional neural network model Um_Net proposed by the research method of improving the recognition and classification accuracy in this paper, after training with an epoch of 50 iterations, The accuracy, loss and number of parameters of AlexNet network model and Um_Net network model on the test set are recorded as shown in Table 2. Figure 9 shows the accuracy curve of AlexNet network model and Um_Net network model on the test set. As can be seen from the chart, the UmNet network model proposed in this paper combines small convolutional nuclei, convolutional attention mechanism module, BN layer, L2 regularization and other modules, while reducing the number of neurons in the fully connected layer according to the actual situation. After network testing, The test set accuracy of bridge data set and concrete pavement data set increased by 5.74% and 4.18%, and the total number of network parameters decreased by 75.04%. The results show that the Um_Net model has better performance of concrete crack identification and classification and fewer model parameters than the original reference model on the basis of the proposed optimization method of identification and classification accuracy.

Table 2 AlexNet and Um_Net test accuracy, loss, number of parameters

Data set	model	Accuracy Acc%	Loss	Parameter number
Beam member	AlexNet	87.31	0.5047	58267714
	Um_Net	93.05	0.4142	14545652
Concrete pavement	AlexNet	89.69	0.4049	58267714
	Um_Net	93.87	0.3659	14542652



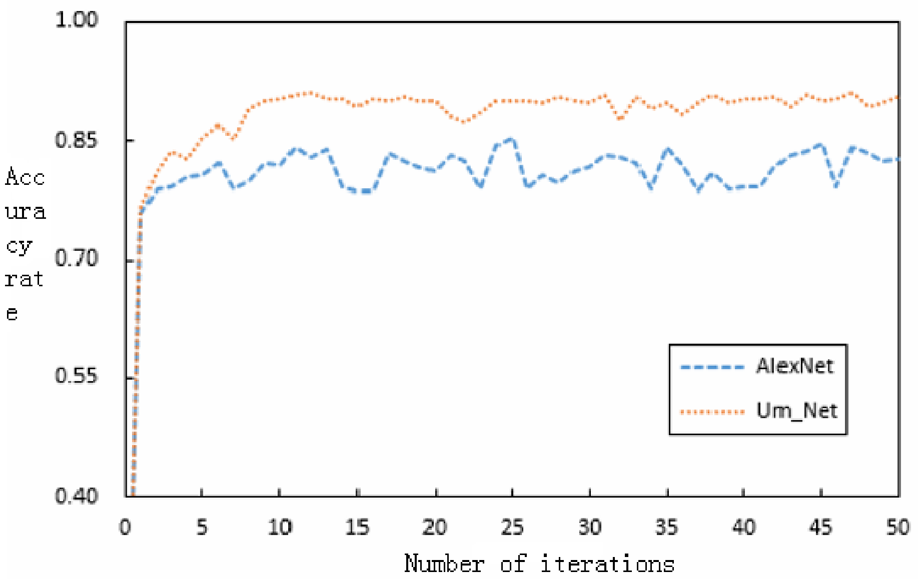


Figure 9 Test accuracy curve of AlexNet and Um_Net (from top to bottom are beam cracks and pavement cracks)

CONCLUSION

In summary, this study aims to explore the neural network optimization algorithm for concrete crack image recognition. Firstly, the classical crack image recognition and classification algorithm model is introduced, and the software and hardware environment of crack recognition and classification is built by TensorFlow2.0 deep learning framework. The classical convolutional neural network AlexNet is used as the reference model to study the optimization method of identification and classification accuracy of the concrete crack data set in Section 3.3. In this paper, convolutional neural network is used to complete the algorithm process of image classification, and an optimization strategy which can improve the accuracy of concrete crack recognition and classification is developed. After comparing the accuracy of crack identification and classification models through actual tests, it is found that on the basis of the limited amount and poor quality of existing concrete crack image data, the overfitting problem can still be dealt with by relying on the structure of the network itself (including increasing the number and scale of convolutional neural networks, adjusting the neuron structure of each layer, etc.), and other components (such as attention module) can be added to further improve the performance. On the basis of the above research, an improved convolutional neural network model Um_Net for concrete crack identification and classification is proposed to achieve accurate location and classification of concrete cracks. This research can provide a more accurate and effective neural network optimization scheme for the field of concrete crack identification, and then improve the safety and durability of concrete buildings in China.

FUNDING

2023 Chongqing Municipal Education Commission Science and Technology Research Program

(KJQN202303238).

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

All authors were fully informed of the study details and made fully informed decisions regarding their participation in this research.

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