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Automatic detection method of bridge cracks based on residual network

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Abstract. At present, the level of bridge crack detection is not high. In order to solve the problems of weak robustness of traditional image processing methods and time-consuming and laborious manual detection, a pixel level detection algorithm of bridge cracks based on adding residual block is proposed, which provides more intuitive and accurate detection results for bridge health assessment. Firstly, the concrete beam slab crack data set with a certain amount of data is built to train and test the model. After comparing and analyzing the four learning rates, 2×10^{-4} is chosen as the initial learning rate. Finally, in the aspect of fracture segmentation, the model proposed in this paper has good performance and good crack identification effect. It can accurately and efficiently locate, classify and identify fractures, which has certain practical application value.

1. Introduction

In order to meet the needs of railway transportation and highway development, a large number of bridges have been built in China. Among them, most of the bridge construction is mainly concrete beam bridges. In the process of long-term use, it will be squeezed by vehicles, at the same time, the performance of the materials used will also deteriorate, resulting in cracks in the bridge floor, which has a major safety hazard^[1]. Therefore, regular crack detection plays a key role in the maintenance and operation of the bridge^[2]. The traditional bridge crack detection is mainly based on manual measurement, which has low efficiency, high rate of missed detection, time-consuming, labor-intensive, and high cost. Therefore, automatic and efficient crack detection is essential to the health assessment of bridge structures.

At present, the automatic crack detection method based on computer vision has been widely concerned. Most of them use digital image processing technology and machine learning algorithm to detect some simple types of structural damage^[3]. Ronneberger et al.^[4] first proposed the UNET model, which is a full convolution neural network model for image segmentation. Due to the advantages of small sample size, fast detection and accurate recognition, UNET network has also been applied in other fields in recent years, such as road detection^[5], remote sensing image semantic segmentation^[6].



Therefore, this paper applies the Unet network with residual module to bridge crack detection, and proposes a bridge crack identification method, which provides certain help for the realization of bridge automatic identification.

2. Network Structure

Semantic segmentation is one of the important research directions in the field of target detection, which can achieve pixel-level target detection. Semantic segmentation is composed of encoder and decoder. The encoder uses convolutional layer to input image features, and adopts pooling layer method to reduce the size and speed of feature reading and reduce the burden of network calculation. The decoder uses the deconvolution method to restore the feature image to the input image size and predict the result. In this paper, the Residual module is added to the Unet network, and the bridge cracks are identified and detected. Separate crack pixels and background pixels from the input image.

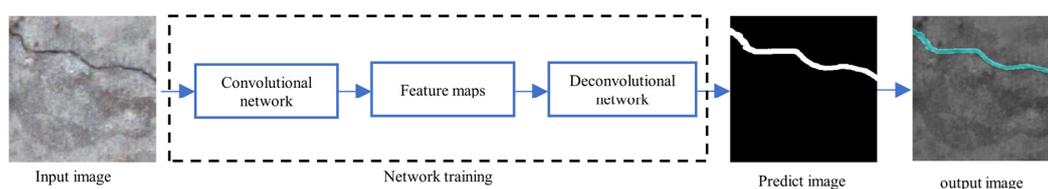


Figure 1. Schematic diagram of crack detection

3. Experiment

3.1. Image source

More than 200 county road bridges and large rural bridges on the main roads of Dongyang City in Zhejiang Province are investigated for one month. The consumer grade Camera Canon PowerShot sx620 HS equipment is used, and the photos are taken by professional bridge inspection engineers. The shooting time is from 8:00 a.m. to 5:00 p.m. This paper mainly collects the photo information of bridge beam and slab crack. The saved image format is. JPG, and the unified saved pixels are 5184 pixels \times 3888 pixels.

3.2. Experimental setup

The model is built by tensorflow and keras, which are open source deep learning frameworks. The virtual Python environment of Res Unet network is established by anaconda. CUDA and cudnn are used to accelerate GPU calculation, so as to improve the training speed of the network. Training, validation and testing are performed on a computer with a 6GB GPU.

3.3. Experimental setup

Because the principle of semantic segmentation is to achieve pixel level detection by classifying each pixel, rather than the whole image classification. The batch size of Res Unet network training is 4, the momentum is 0.99, the weight delay is 0.000001, the beta1 is 0.7, the beta2 is 0.999, the epsilon is 10^{-8} , a total of 200 cycles. With the increasing depth of deep convolutional network, overfitting is likely to occur when the number of training samples is insufficient. In order to solve the whole problem, Sigmoid is introduced as the linear activation function. Since its gradient is always between 0 and 1, there is no problem of the gradient disappearing. Adam was selected as the optimization tool, and the adaptive time estimation method was adopted to calculate the adaptive learning rate of each parameter to accelerate the convergence speed.

3.4. Network evaluation index

In this paper, objective evaluation criteria are used to evaluate the effect of crack recognition: Precision and Recall are used as evaluation indexes of image segmentation results. F1 is used as evaluation value of Precision and Recall rate. IOU is used as the standard of crack detection accuracy.

- Precision = $\frac{TP}{TP + FP}$
- Recall = $\frac{TP}{TP + FN}$
- $F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$
- IoU = $\frac{TP}{TP + FN + FP}$

Where TP represents correctly segmented crack pixels; FP represents incorrectly segmented crack pixels; FN represents missing segmented crack pixels; TN represents correctly predicted background pixels.

4. Results and discussion

4.1. Training results

After setting the parameters, the network parameters were trained. 1069 training sets and 633 verification sets were involved. In order to prevent over fitting and make the model more robust. At the same time, the method of data expansion is used, including random clipping, horizontal flipping, translation, random brightness contrast, etc. to expand the data set to 6 times. In order to save time, set up early stop program, a total of 240 epochs. In each iteration, the current network training loss is calculated and the weight is saved.

This paper selects a better initial learning rate by comparing the learning rate, and then compares and analyzes the subjective and objective indicators. The objective evaluation criteria are mainly based on Precision and Recall. The subjective evaluation standard compares the fracture segmentation of the original drawing, the label map and the prediction map, and then compares the horizontal and vertical details.

4.2. Comparative analysis of learning rate

When gradient descent is carried out for optimization, learning rate plays a crucial role in weight updating. Therefore, the influence of learning rate on the model is firstly compared, and the four learning rates are respectively 2×10^{-3} , 2×10^{-4} , 2×10^{-5} , 2×10^{-6} . It can be seen from Figure 2 that after the first round of iteration, the Loss with learning rate of 2×10^{-3} and 2×10^{-4} directly decreased to below 0.40, and the others are 0.50 and 0.80 in turn. Therefore, the learning rate of the first iteration was relatively large and the effect was significant. In terms of the decline process, the first thing that tends to be stable is to select a smaller learning rate, which has the fastest convergence speed, the best performance, and the largest decline, which will greatly improve the recognition speed.

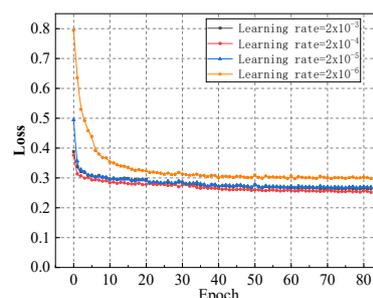


Figure 2. Training loss under different learning rates.

Figure 3 shows the changes in the accuracy of each learning rate, comprehensive evaluation indicators, cross-to-match ratio, and recall rate. These performance indicators are consistent with the changes in the loss function. Before 10 epochs, all indicators rose rapidly, and gradually stabilized after 20 epochs. Similar results can be obtained when the learning rate is 2×10^{-4} or 2×10^{-5} , and the former performs slightly better. When the learning rate is 2×10^{-6} , the effect is much worse than the previous two, especially the recall rate, which fluctuates greatly, which may be caused by the over-fitting phenomenon due to the low learning rate. After comprehensive comparison, 2×10^{-4} with the best performance is selected as the initial learning rate.

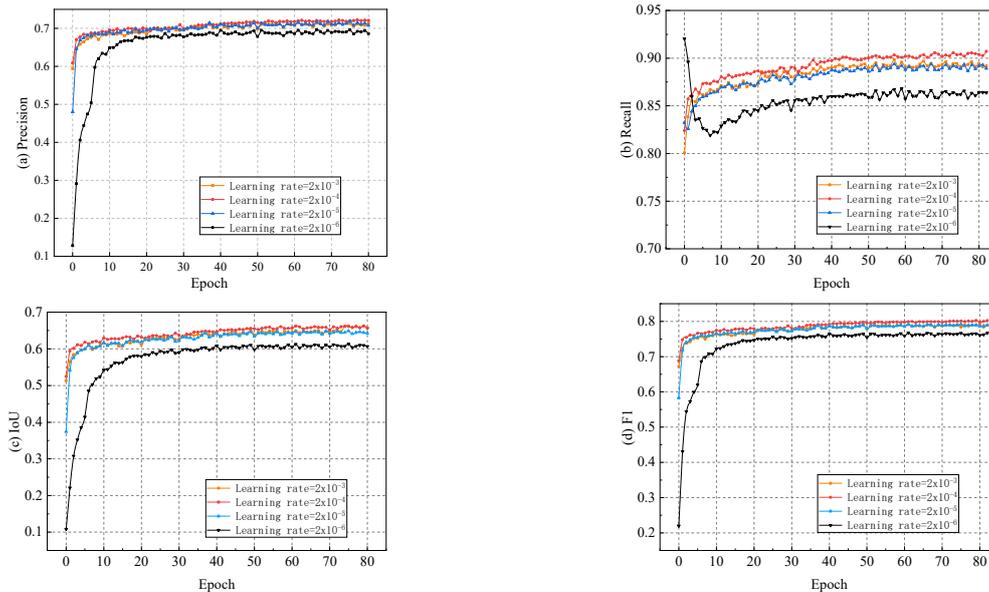
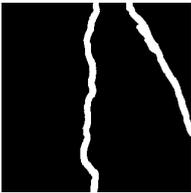
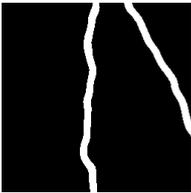
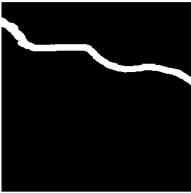
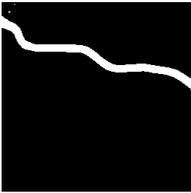


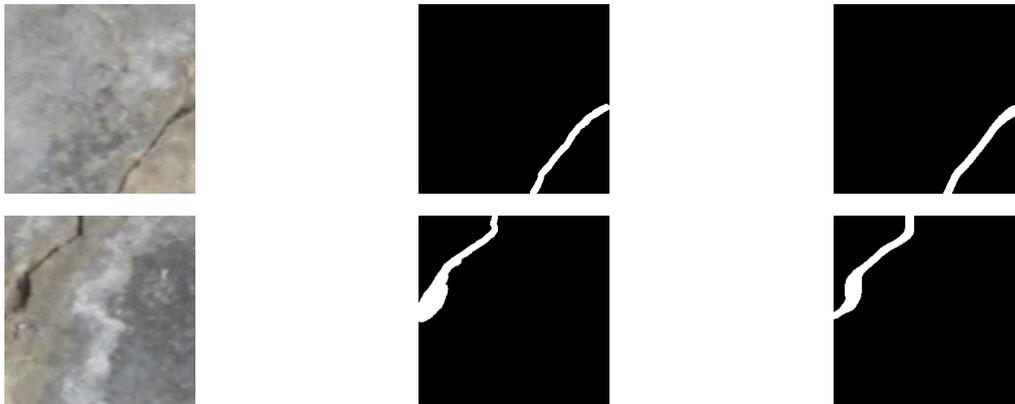
Figure 3. The evaluation index: (a) Precision, (b) Recall, (c) IoU, (d) F1.

4.3. Results and discussion

Objective data show that the performance of Res Unet model is perfect, but the final effect judgment needs to be determined by comparing the output images. Part of the recognition results are shown in Table 1. The original image, label image and output image are compared respectively. The model has a good effect on the identification of fine fractures, and the identification map is basically consistent with the label map. For the different recognition performance of the coarse fracture, the crack shadow is marked as crack in the label map, but the recognition result is identified as non crack. This needs to be further explored.

Table 1. Effect picture of crack identification.

Original image	Label map	Res Unet
		
		



5. Conclusion

In this paper, the principle of full convolution neural network technology to identify crack information is described. Aiming at the problem of bridge crack identification, the program of crack identification is written by Python language

(1) The data set of bridge crack disease is collected by consumer camera manually, and the image data is normalized and labeled. The training database is constructed for network model training. However, the amount of data is far from enough, and more samples need to be collected in the future.

(2) Aiming at the problems existing in the research of bridge automatic identification, an improved UNET model with residual block is proposed. The learning rate is compared. The results show that the method proposed in this paper can detect bridge cracks more accurately.

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