Road and Bridge Expansion Joint Crack Detection and Disease Classification Based on Deep Learning and Morphology

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Abstract. Roads and bridges play a pivotal role in China's land transportation. However, with the increase in operation time, the concrete in the anchorage area of road and bridge expansion joints will be subjected to fatigue loading for a long time cracking will occur, and the expansion joints will be bulging and other diseases. In turn, it may lead to a major accident. To quickly detect whether there are cracks on the surface around the road and bridge expansion joints and the type of cracks, a road and bridge expansion joint crack classification model was established. The experimental results show that the accuracy of the model reaches 98.97% after three iteration cycles, and the loss value is less than 0.06. Then, morphological filtering algorithms based on the computer vision framework OpenCV were used to calculate the maximum width, average width, and average angle of the cracks. This can be used to categorize the degree of crack damage in road and bridge expansion joints. Finally, through experimental testing, the relative error between the crack width value and the actual value measured by the reading microscope is within 3%.

Keywords: Deep learning, Morphological filtering, Crack detection and classification.

1 Introduction

Road and bridge expansion joints are accessory structures to ensure a stable transition between bridge construction and the built-in structure. To a certain extent, it can play the role of sharing the external force and maintaining the stability of the building. However, as the road and bridge operation time passes, the concrete in the anchorage area next to the expansion joint device will be subjected to fatigue loading for a long time to produce cracking and other phenomena. The longitudinal cracks, transverse, or mesh cracks in the concrete in the anchorage area are classified as mild, moderate, and severe according to the width of the cracks [1]. If the crack width of concrete cracking in the anchorage area of road and bridge expansion joints can be monitored in real-time and

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repaired in time before it reaches its peak, traffic accidents caused by expansion joint diseases can be prevented.

In recent years, deep learning has been widely used in the field of image recognition. A deep learning algorithm can quickly and accurately detect whether there is a crack disease in road and bridge expansion joints. Therefore, to quickly identify whether there are cracks near the bridge expansion joint, a bridge expansion joint crack recognition network was constructed based on the TensorFlow framework developed by Google. Then, to further classify the crack disease degree, Based on the morphological filtering algorithm in the computer vision framework OpenCV to calculate the maximum width, average width, and average angle of the cracks near the expansion joints of road and bridge. The main contributions of this paper can be summarized as follows.

(1) A road and bridge expansion joint crack recognition network was established based on the TensorFlow framework, which can quickly discern whether cracks exist in the anchorage area of road and bridge expansion joints.

(2) Morphological filtering algorithms based on the computer vision framework OpenCV were used to calculate the maximum value of the width as well as the average value of the width and the average value of the angle of each crack in the anchorage zone of the expansion joints of the road and bridge and to categorize the degree of crack disease.

(3) The combination of deep learning and filtering algorithms effectively accomplishes the detection and classification of road and bridge expansion joint cracks and the degree of disease. Compared with traditional detection methods, it is not only low-cost but also high efficiency.

2 Literature review

Crack detection methods have blossomed over the past decade or so. From image-based processing to deep learning. Whereas image processing is widely used for crack segmentation, deep learning methods excel in crack detection and classification.

Many researchers have attempted to extract road crack features such as length, width, and angle for crack detection and classification by image processing methods. Zhu et al. [2] developed a system to retrieve concrete crack attributes such as length, direction, and width for automatic assessment of structural conditions after an earthquake. Liu et al. [3] proposed a method for automatic crack assessment through image adaptive processing, which utilizes a median filter to separate the skeleton and edges of a crack. Shao et al. [4] proposed a two-dimensional Otsu thresholding segmentation method based on hybrid particle swarm optimization for segmenting crack images. Xie et al. [5] proposed a crack width measurement method based on orthogonal skeleton lines. The crack image is grayscaled and then median filtered and thresholded segmented. Finally, the skeleton and contour of the crack image are extracted using this method to complete the measurement and comparison between the simulated crack and the actual crack.

With the wide range of applications achieved by deep learning, especially convolutional neural networks (CNN) in deep learning in the field of image recognition, numerous academics are trying to use CNN to detect and classify bridge cracks. Dung et al. [6] proposed a semantic segmentation crack detection method based on fully convolutional networks (FCN). The authors deployed VGG-16 as an encoder for the FCN model. The FCN model was trained by using 600 annotated images, and the model successfully detected cracked and non-cracked pixels on concrete images with an average accuracy of 90%. Flah et al. [7] proposed a classifier based on CNN and Otsu images. It was used to determine if a crack exists and where it exists. Additionally, it successfully quantifies the length, width, and angle of the crack. The authors trained the model with 20,000 images and achieved 96.17% accuracy. Hac et al. [8] proposed the use of fast R-CNN for crack detection that can quickly replenish image cracks in concrete pavements. Inam et al. [9] proposed a two-stage intelligent infrastructure management framework. First, a variant of the YOLOv5 model is used to detect cracks and evaluate the degree of cracking. The output mask of U-Net is applied to the attribute extractor to calculate the width, height, and area of the crack in pixels.

The above literature shows that the use of CNN to recognize bridge cracks not only has high recognition accuracy but also has a short training time and small memory occupation, which can be well applied to actual bridge crack detection. As for the extraction of crack features, most of the researchers have extracted the cracks by the filtering method. The skeleton lines and edges of the cracks are found first, and then the crack width, area, angle, etc. are calculated. Based on the inspiration of the above literature, deep learning, and filtering algorithms will be combined to accomplish the road and bridge expansion joint crack detection and disease degree classification.

3 Road and bridge expansion joint crack identification model based on CNN

3.1 Datasets

Bridge crack data from image data provided in the literature [10] was used. A total of 4000 images with 227 x 227 pixel RGB channels were selected. There are 2000 images of road and bridge expansion joint cracks and 2000 images of non-cracked road and bridge expansion joints. Finally, the data set is divided into the training set, test set, and validation set in the ratio of 7:2:1.

3.2 Data pre-processing

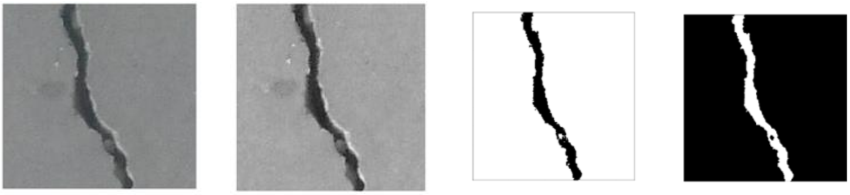
A morphology filter is used to extract the cracks in the image. These steps are as follows.

(1) Grey Processing: First, images are grayscaled. This simplifies the image matrix, making the image take up less memory and run faster. Moreover, the grayed image can visually increase the contrast and highlight the target area. The result is shown as (b) in Figure 1.

(2) Sauvola Binarization: Sauvola is an image binarization method that considers the local mean luminance. It takes the current pixel point as the center and dynamically

calculates the threshold value of that pixel point based on the mean and standard variance of the grayscale in the neighborhood of the current pixel point. The result is shown as (c) in Figure 1.

(3) Closed Operation: To effectively remove some isolated noise points and a few burrs present in the crack image after binarization, the closed operation in morphology is used to denoise them. The closed operation is a combination of expansion and erosion, where expansion is performed first followed by erosion. It can erase the darker small cavity pixels, and the effect is shown as (d) in Figure 1.



(a) (b) (c) (d)

Fig. 1. Image pre-processing.

3.3 Establishment of model

The model of crack identification proposed in this paper uses 3 convolutional layers (C1, C3, C5), 3 maximum pooling layers (S2, S4, S6), 1 flat layer (F7), and 2 fully connected layers. A dropout layer (0.5) is added after F7. About the use of activation functions, the ReLU activation function is added after C1, C3, C5, and F7. The sigmoid activation function is added in the last layer. The last layer outputs the recognition probability value of whether the image is a crack or not. Where the number of convolution kernels starts from 32 and the bias term value is initialized to 0.1. The schematic diagram of the whole network structure of the model is shown in Figure 2.

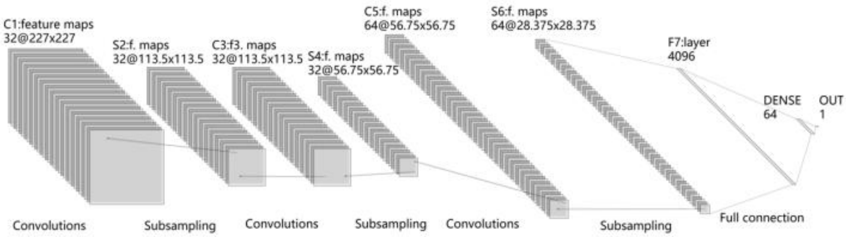


Fig. 2. Model network structure.

3.4 Training and testing of the model

The model training parameters are shown in Table 1. The detailed parameters of the optimizer rmsprop are shown in Table 2. The accuracy of the model is 98.97% after three iteration cycles, and the loss value is less than 0.06. In addition, the total training time of the model is 20.98s. It is easy to find that the proposed model has high accuracy and good stability. Better still, it has low training difficulty and takes up little memory.

Finally, the model is tested. The test set contains 800 mixed cracked and non-cracked maps. The test results are shown in Table 3.

Table 1. Parameters of the model training.

Epoch	BatchSize	Optimizer	Loss Function
3	10	Rmsprop	Binary Crossentropy

Table 2. Parameters of the model training.

Lr	Rho	Epsilon	Decay
0.001	0.9	None	0.0

Table 3. Parameters of the model training.

Final Accuracy	Final Loss	Time Taken(Seconds)
97.25%	0.1232	20.98

3.5 Comparison experiments

Then, the proposed model is compared with the traditional VGG-16 model for experiments. The results are compared after 20 iterative cycles under the same conditions. The obtained accuracy and loss values are shown in Figure 3 and Figure 4.

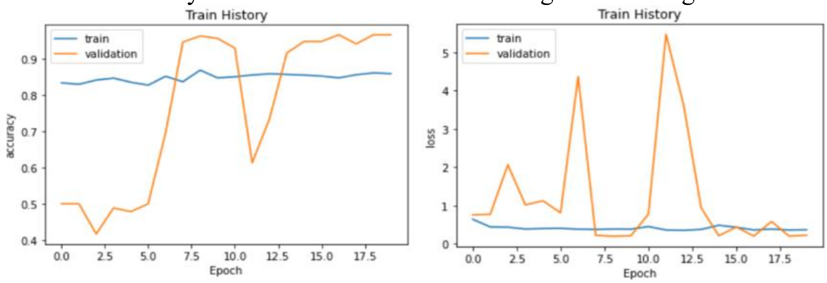


Fig. 3. Training accuracy and loss of VGG-16.

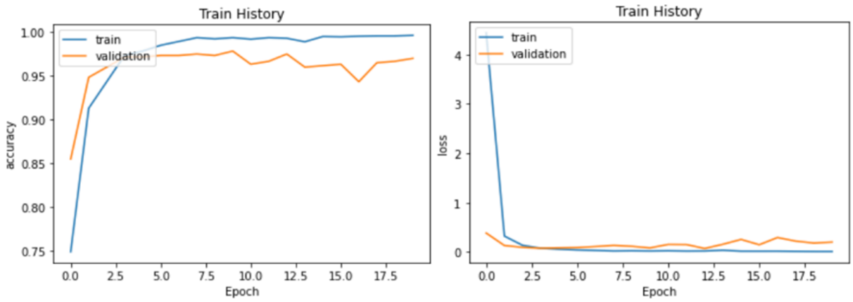


Fig. 4. Training accuracy and loss of the model proposed in this paper.

Collectively, the proposed model outperforms VGG-16 in terms of 20 iterative cycles, and the proposed model is more usable than the edge devices. It has the advantages of low load, easy training, better stability, and higher accuracy.

4 Disease classification

4.1 Classification criteria for crack disease

The grade assessment of crack damage is according to the literature [2]. Since there is no grade rating for the serious level of potholes, to facilitate our assessment of the disease at the expansion joint of the road and bridge, we set the crack width greater than 20 mm are pothole damage that is deteriorating concrete. The specific road technical condition assessment criteria are shown in Table 4.

Table 4. The standard of disease degree.

Disease Degree	Standard
Mild	<3 mm
Moderate	3 mm ~10mm
Severe	10 mm~20mm
Deteriorating Concrete	>20mm

4.2 Extraction process of the crack feature

The steps for extraction of crack features are as follows.

1) Crack slitting: Branching points of cracks are detected and collected. A window with a given size is generated with the branch point as the center. Then, the intersection point of each center line with the edge of the window is taken. If the number of points is less than 3, the window is too large. Therefore, it is necessary to minimize the initial value of all window sizes until the number of points equals 3. Also, consider the minimum size of the window to avoid cutting non-small branches. The result of the cut branching is shown in (a) in Figure 5.

2) Crack labeling: The input crack image is labeled to obtain the area and label of the cracks. Specifically, the input binarized image is labeled with the connected area, and information such as slice, area, and label of the labeled connected area is obtained. The schematic diagram after labeling is shown in (b) in Figure 5.

3) Crack noise reduction: For each crack area, obtain its area and calculate the area with its outer circle as the standard, get the ratio F between its area and the standard area, and delete the area whose ratio is greater than the set threshold (the threshold is set to 0.1).

4) Crack skeletonization: The remaining crack area is skeletonized to get its centerline. The result is shown in (c) in Figure 5.

5) Angle calculation: According to the set angle filters (fil_0, fil_30, fil_60, fil_90, fil_120, fil_150), convolution is performed on each centerline pixel to obtain the response value of that pixel at different angles.

6) Width calculation: The width and angle of the crack corresponding to each centerline pixel are calculated from the response values. By averaging all the widths and angles, the average width and average angle are obtained. Specifically, after obtaining the centerline pixels by skeletonization, the centerline width is calculated according to equation (1). Finally, after obtaining the centerline width for each point, the calibration factor X is multiplied by the true crack width.

$$W = \left(\frac{4 * S}{\pi} \right)^{1/2} \tag{1}$$

W represents the width, and S represents the crack area.

7) Results show: The results are shown in: The area of the crack, the maximum value of the width, the average value of the width, and the average value of the angle are stored in the Pandas DataFrame and returned. The results are shown in Table 5. The width of the crack, which is the maximum value of the width, is used as a criterion to categorize the disease. From Table 5, it can be seen that the maximum width is 20.821 > 20 mm which is classified as deteriorated concrete.

(a) (b) (c)

Fig. 5. The extraction process of the crack feature.

Table 5. Result show.

ID	Crack Area	Max Width	Mean Width	Mean Angle
0	(1, (slice(0, 156, None), slice(67, 123, None)))	20.821 mm	13.099 mm	84.605°
1	(3, (slice(157, 179, None), slice(116, 127, None)))	6.493 mm	4.684 mm	91.500°

4.3 Experimental validation

To verify the feasibility and accuracy of the crack detection method in this paper, experimental tests were conducted at different locations in the anchorage zones of roadway and bridge expansion joints, respectively. Crack images were taken at 30 cm, 50 cm, and 70 cm from the ground. The actual width values were measured with a 100x reading microscope (with an accuracy of 0.02 mm) and compared with the values calculated using the algorithm in this paper. The results are shown in Table 6.

Table 6. Comparison of theoretical and actual values of crack width.

Distance	Theoretical Values	Actual Values	Error	Relative Error
30cm	0.853 mm	0.829 mm	0.024 mm	2.80%
50cm	1.027 mm	1.014 mm	0.013 mm	1.27%
70cm	1.552 mm	1.509 mm	0.043 mm	2.77%

5 Conclusion

In this paper, a road and bridge expansion joint crack recognition model is proposed for quickly discriminating the presence of cracks in images. In addition, a road and bridge expansion joint crack classification model was established. A filtering algorithm is utilized to extract crack features as a way to classify the degree of crack distress. Through experimental measurements, the crack recognition model proposed in this paper is easier to train, occupies less memory, and has higher recognition accuracy than general deep learning networks. The relative error of calculating crack width using the filtering algorithm in this paper is around 3%, which has high accuracy and can be applied in practice. In future work, the method studied in this paper can be deployed on road and bridge inspection robots to reduce the labor and material resources for inspection.

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