DeepLabV3+ Based Mask R-CNN for Crack Detection and Segmentation in Concrete Structures

Yuewei Liu
School of Civil Engineering and Architecture, Wenzhou Polytechnic, Zhejiang, 325000, China

Abstract—**In order to solve the problem of concrete structure crack detection and segmentation and improve the efficiency of detection and segmentation, this paper proposes a crack detection and segmentation method for concrete structure based on DeepLabV3+ and Mask R-CNN algorithm. Firstly, a crack detection and segmentation scheme is designed by analysing the crack detection and segmentation problem of concrete structure. Secondly, a crack detection method based on Mask R-CNN algorithm is proposed for the crack detection problem of concrete structure. Then, a crack segmentation method based on DeepLabV3+ algorithm is proposed for the crack segmentation problem of concrete structure. Finally, bridge crack image data is used for the crack detection and segmentation of concrete structure. Finally, the concrete structure crack detection and segmentation method is validated and analysed using bridge crack image data. The results show that the Mask R-CNN model has better performance in the localisation and identification of cracks, and the DeepLabV3+ model has higher accuracy and contour extraction integrity in solving the crack segmentation problem.**

Keywords—DeepLabV3+; Mask R-CNN; concrete structure; crack detection and segmentation; deep learning algorithm

I. Introduction

With the rapid development of the society, the state's investment in infrastructure such as roads, bridges and buildings is increasing [1]. Most of the above infrastructures are composed of concrete. And the concrete structure may produce cracks for various reasons, which has a great impact on its subsequent use as well as safety [2]. The causes of cracks in concrete facilities include the following: 1) thermal expansion and contraction of concrete produces a large number of cracks; 2) frequent vehicle trips put a great deal of pressure on the highway nucleus bridges, resulting in cracks; 3) too high or too low a standard of concrete ratios cause cracks in the structure; and 4) improper construction causes the concrete shrinkage nucleus to crack prematurely. If the concrete cracks are not repaired in time may lead to highway fracture, bridge nuclear construction facilities collapse, endangering traffic travel [3]. Traditional concrete crack detection and maintenance using manual methods, not only consume manpower and material resources, but also inaccurate detection results, high risk, easy to accident [3]. In order to facilitate the detection of concrete crack nuclei to reduce the risk of detection, artificial intelligence technology is used, not only to improve the traditional image processing technology problems, but also to detect the good results [4]. Concrete structure crack detection and segmentation research is mainly divided into concrete crack detection, crack segmentation and other issues research. The current concrete crack detection methods are divided into contact detection method, non-contact detection method, and image crack detection method [5-7]. Contact detection method is generally manual detection method, is through visual inspection or measurement attack to detect and record the crack size and location, this method is simple, but has great limitations [5]. Non-contact detection methods are generally used to detect cracks with the help of existing infrared, radar and other equipment, the use of which not only does not have a bad effect on the concrete being detected, but also solves the problem of losses due to human error in judgment [6]. Image crack detection method mainly uses image segmentation technology to detect concrete cracks, which includes segmentation algorithms such as thresholding, region growing, edge detection, etc. This method has the advantages of high detection efficiency and low cost [7]. Xiao et al. [8] proposed the histogram bimodal method to segment the image. Xi et al. [9] proposed the OTUS algorithm to detect cracks, which not only can effectively detect small and irregular cracks, but also the detection accuracy reaches 85%. Li and Yang [10] used osmotic hair to detect the concrete cracks, and got a better result. Moezi et al. [11] combined the seepage theory with the adaptive Canny operator to improve the effect of the detection algorithm. Although the traditional data image detection method is low cost and simple to operate, it is only adapted to simple environments, and the detection segmentation results are not ideal. With the development of artificial intelligence technology, deep learning algorithms are introduced into the image crack detection segmentation problem. Cha et al. [12] used deep learning technology CNN to identify cracks on building surfaces, and achieved 98% accuracy. Zhang et al. [13] used Mask-RCNN combined with FPN feature pyramid network module kernel Resnet model to improve the extraction accuracy of crack disease features, and showed a better recognition accuracy. Li et al [14] for the problem of extracting cracks on concrete surfaces, and proposed an improved lightweight global convolutional network image segmentation model for pavement cracks. Kim and Cho [15] uses the PSPNet semantic segmentation platform for model detection of highway bridge cracks, which shows good detection results.

Although these methods have made significant progress in improving the accuracy and efficiency of crack detection, there are still some shortcomings [16]: (1) the segmentation models suffer from the presence of pooling layers, which leads to the loss of some positional information, restricting their ability to accurately identify fine cracks; (2) some of the structures sacrifice the feature resolution in successive pooling operations or convolutional steps, which makes the prediction task limited and affecting the performance of image segmentation; (3) various types of detection models still need to be further verified for their performance and stability in practical applications.

Concrete crack detection and segmentation is crucial to ensure the safety of concrete structures. For the current concrete crack detection and segmentation problems, this paper proposes Mask R-CNN [18] based on DeepLabV3+ [17] for concrete structure crack detection and segmentation, and the specific contributions of the paper are as follows: (1) analyse the concrete structure crack detection and segmentation problems, and put forward the research scheme; (2) around the concrete structure crack detection problems, put forward the concrete structure crack detection model based on the Mask R-CNN algorithm; (3) A crack segmentation model based on DeepLabV3+ algorithm is proposed for the concrete structure crack segmentation problem; (4) The proposed method is analysed and validated using concrete crack data, and the results show that the model method improves the detection efficiency and accuracy of concrete.

II. Crack Detection and Segmentation in Concrete Structures

A. Analysis of the Problem

As one of the common defects in concrete structures, cracks have a direct impact on the safety and durability of bridges. The detailed analysis of cracks in concrete bridges (Fig. 1) can provide a comprehensive understanding of the health status of bridge structures and provide a scientific basis for timely maintenance and repair of bridges [19].

Fig. 1. Schematic diagram of concrete bridge cracks

Concrete crack characteristics mainly include: 1) crack morphology and distribution, which mainly reflects the bridge structure force and deformation process; 2) crack size and shape, the size of which is directly related to the degree of damage to the structure, and its distribution pattern can reflect the structural uneven force, deformation inconsistency and so on, as shown in Fig. 2.

For the task of crack detection in concrete bridges, the concern is the morphology of the cracks. Currently, according to the morphology, concrete cracks are classified into linear cracks and web-like cracks (Fig. 3). Deep learning algorithm-based crack detection method for concrete bridges needs to be targeted at different scales, can effectively detect cracks of various sizes and shapes, and can cope with different lighting conditions and environmental changes, the specific analysis is shown in Fig. 4.

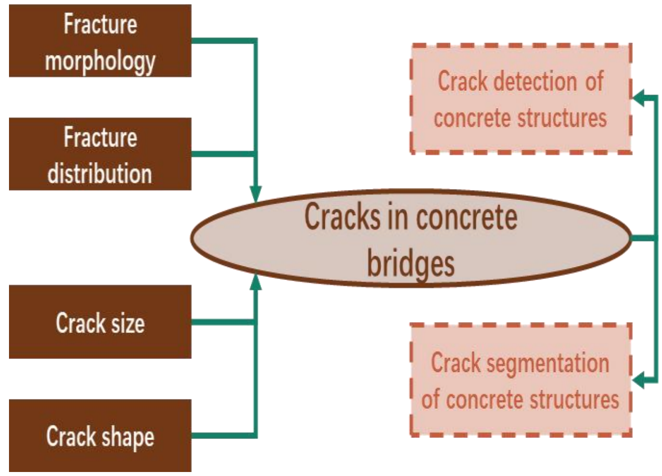


Fig. 2. Characteristics analysis of cracks in concrete bridges.

(a) Straight cracks.

(b) Reticulated cracks.

Fig. 3. Concrete bridge crack patterns.

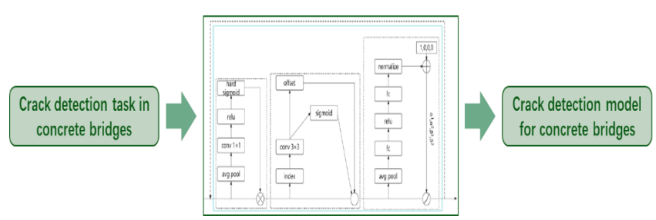


Fig. 4. Concrete bridge crack detection problem analysis.

In the task of concrete bridge crack detection, only crack target detection is not enough, and the introduction of image segmentation model based on deep learning is crucial. The concrete bridge crack segmentation study is not only able to accurately locate each crack, but also able to accurately segment the outline of the crack, which is analysed as shown in Fig. 5.

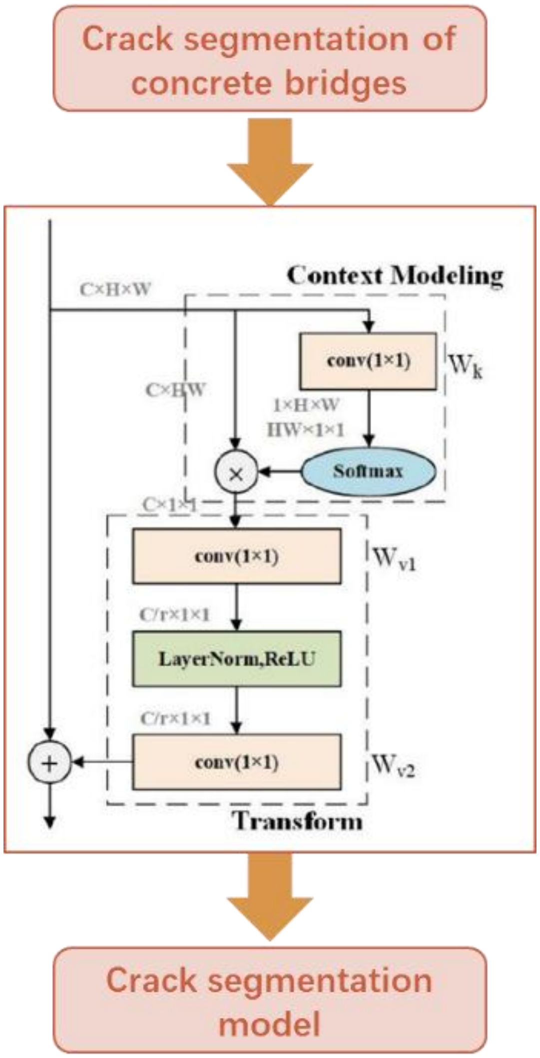


Fig. 5. Analysing crack segmentation problems in concrete bridges.

B. Design of Crack Detection and Segmentation Programmes for Concrete Structures

According to the analysis of concrete structure crack detection and segmentation problem, this paper adopts deep learning algorithm to construct concrete structure crack detection and segmentation model, the specific design scheme is shown in Fig. 6. Concrete structure crack detection and segmentation scheme design from two modules to study the concrete structure crack analysis problem, the first module is the concrete structure crack detection model construction, using deep learning algorithms (Mask R-CNN) to locate the overall location of the crack; the second module is the concrete structure crack segmentation model construction, using deep learning algorithms (DeepLabV3+) to segment the crack contour of the cracks.

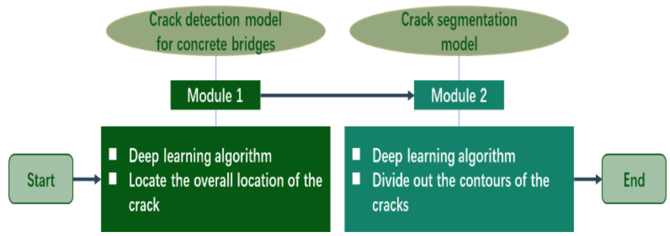
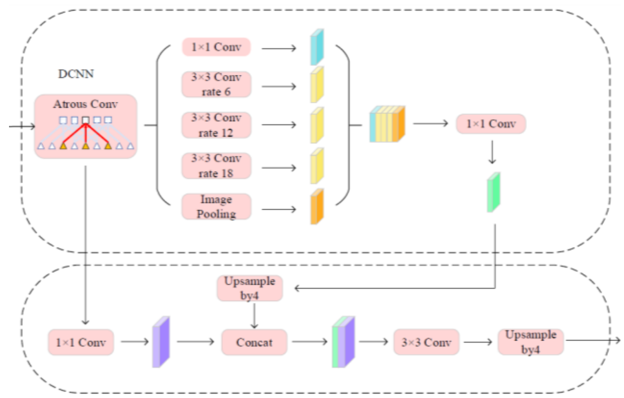


Fig. 6. Programme design.

III. CRACK AND SEGMENTATION OF CONCRETE STRUCTURES DETECTION

A. DeepLabV3+ Algorithm

The DeepLabV3+ algorithm is the latest version of the Deeplab series [20], and the specific structure is shown in Fig. 7. The DeepLabV3+ network model utilises a combination of the spatial pyramid pooling module and the decoder-encoder structure of the deep neural network to achieve fine segmentation of the target boundary. The spatial pyramid pooling module detects input features at multiple rates and multiple effective fields of view through filtering or pooling operations to encode multi-scale contextual information, and the network structure is shown in Fig. 7; the encoder-decoder structure captures clearer target boundaries by gradually reverting to spatial information, and the network diagram is shown in Fig. 8.



DeepLabV3+ algorithm structure.

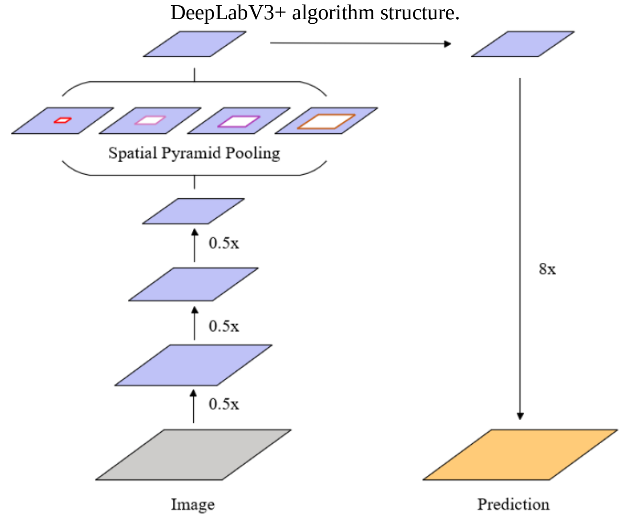


Fig. 7. Encoder-decoder structure network.

The DeepLabV3+ network model structure mainly consists of two parts, Encoder and Decoder. The encoder part of the DeepLabV3+ network uses the DeepLabV3 network as a whole for feature extraction of feature maps of arbitrary resolution output from the deep neural network. The encoder works as follows: first a Conv+BN+ReLU is used, then a convolution, plus global average pooling is used to obtain the scale features, and finally the features are upsampled using Conv+BN+ReLU+bilinear interpolation to keep the feature maps of the same size. The decoder part is spliced using the outputs of the encoder and DCNN parts, and finally a convolution and upsampling is used for the output.

The DeepLabV3+ network model convolution layer effectively reduces the number of parameters in the model, reduces the risk of overfitting, and improves the generalisation of the model [21]. The convolution process (shown in Fig. 8) is as follows:

$$a_{i,j} = F\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} w_{m,n} x_{i+m,j+n}\right) \tag{1}$$

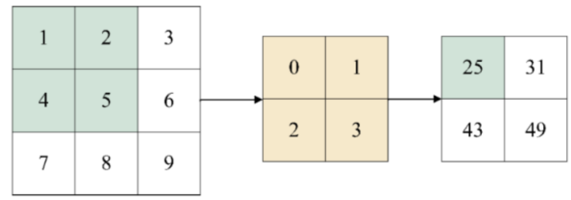


Fig. 8. Convolution process.

Where, $a_{i,j}$ is the feature map element; $x_{i,j}$ is the i-th row and j-th column element in the convolution feature map; $w_{m,n}$ is the m-th row and n-th column ground weight in the convolution; F is the activation function.

B. Mask R-CNN Algorithm

Mask R-CNN algorithm is a deep learning algorithm [22] for target detection and instance segmentation. Fig. 9 extends Faster-RCNN (Convolutional Neural Network based target detection algorithm) by adding a segmentation branch to predict the exact boundary and mask of the target.

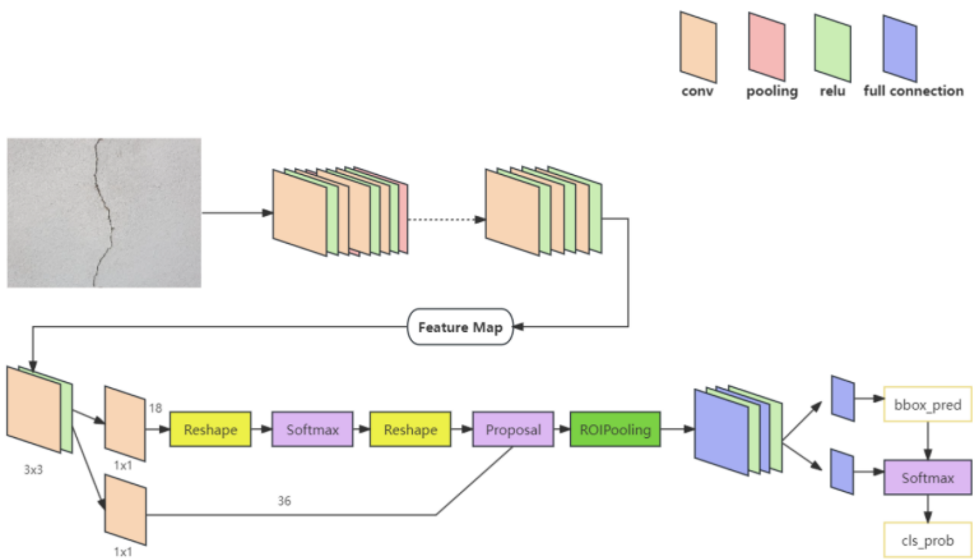


Fig. 9. Mask R-CNN algorithm.

The target detection process of Faster R-CNN is divided into several key steps (shown in Fig. 10):

- (Feature extraction by Convolutional Neural Network (CNN) to obtain high-level semantic information from the input image;
- Introducing a region proposal network (RPN) to generate a large number of candidate target regions, i.e., anchoring boxes, on the convolutional feature map;
- Non-maximal suppression (NMS) is used to eliminate highly overlapping redundant anchor frames, ensuring that each target region is represented by only one candidate frame;
- In the fully connected layer, the Faster R-CNN performs classification and bounding box regression of targets.

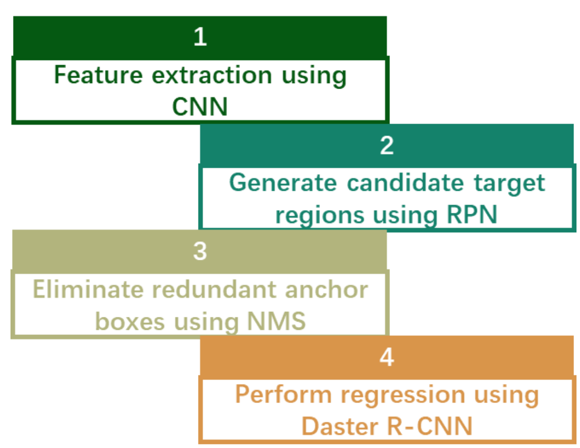


Fig. 10. Steps of Mask R-CNN algorithm.

C. Application of Mask R-CNN Algorithm based on DeepLabV3+

In order to achieve the improvement of the accuracy of concrete structure crack detection and segmentation based on deep learning algorithm, a concrete structure crack detection and segmentation method based on DeepLabV3+ algorithm and Mask R-CNN algorithm is proposed in combination with DeepLabV3+ algorithm and Mask R-CNN algorithm, which is shown in Fig. 11. The application of this concrete structural crack detection and segmentation method is divided into two parts, the first part is the concrete structural crack detection method based on Mask R-CNN algorithm, which is mainly used to automatically and quickly identify and locate the cracks, and the second part is the concrete structural crack segmentation method based on DeepLabV3+ algorithm, which is mainly used to accurately segment the contour of the cracks.

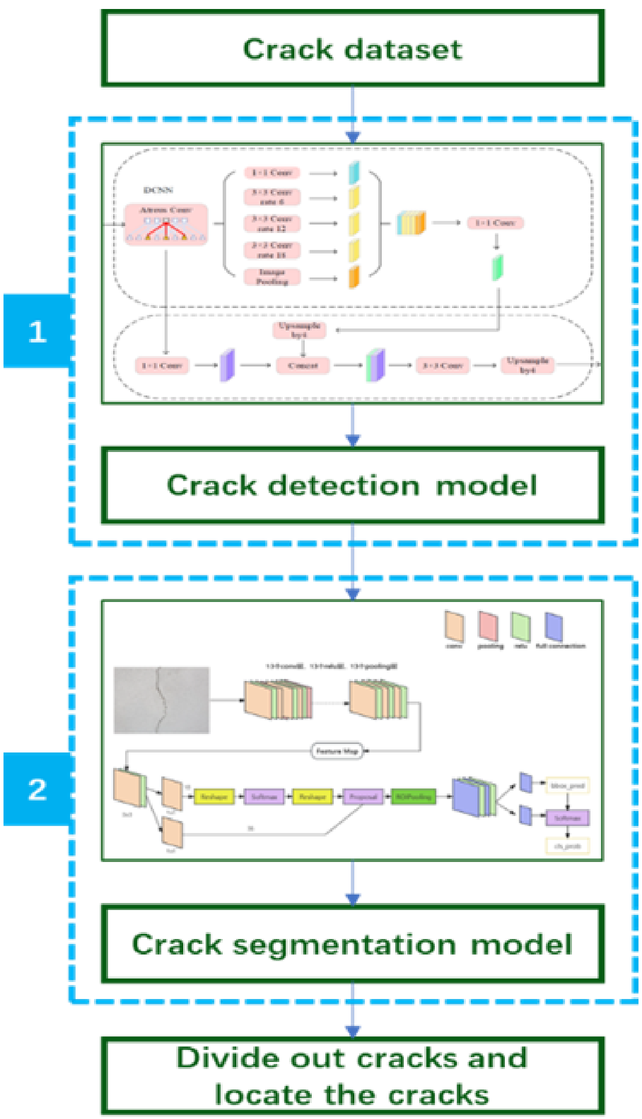


Fig. 11. Application of Mask R-CNN algorithm based on DeepLabV3+.

IV. Simulation Analysis

A. Creation of Crack Data Set

1) Data set collection: In this paper, the validation of crack detection and segmentation algorithms for concrete structures is carried out using bridge crack image data. The bridge concrete crack dataset includes the dataset collected by the intelligent inspection vehicle [23] (Fig. 12) and the public dataset of Roboflow, an annotation platform for AI image recognition model training dataset.

A total of 2016 images of cracks collected through the image acquisition of the intelligent inspection vehicle with the open dataset, which lays the data foundation for the establishment of the subsequent crack-related dataset.

2) Image data enhancement: In order to enrich the dataset so that the model can better learn the crack diversity features, the steps of crack image enhancement [24] are as follows: 1) Enrich the image set with various shapes, sizes and orientations; 2) Simulate the image enhancement in different environments with different lighting conditions, angle changes and noise interference. The schematic of data enhancement is shown in Fig. 13.

3) Image annotation: In order to construct a complete crack detection dataset, the location and shape of crack images need to be labelled. In this paper, Labeling is used to label the crack images [25], and the specific labelling interface is shown in Fig. 14. The steps of concrete structure crack image labelling include the following: 1) load the image into the Labeling image; 2) use the bar box to select the crack and assign the label "crack"; 3) adjust the size and position of the box to ensure that the crack is covered. The label corresponding to the image consists of five numbers, representing the category, the coordinates of the centre of the bounding box (x,y) and the width (w) and height (h) of the bounding box, respectively, and the specific structure of the label is shown in Fig. 15.

The enhanced image data are labelled to construct the final dataset. The dataset consists of 4028 crack images, divided into 7:2:1 ratio, specifically the training set, validation set, and test set, respectively.

Fig. 12. Intelligent crack detection vehicle.

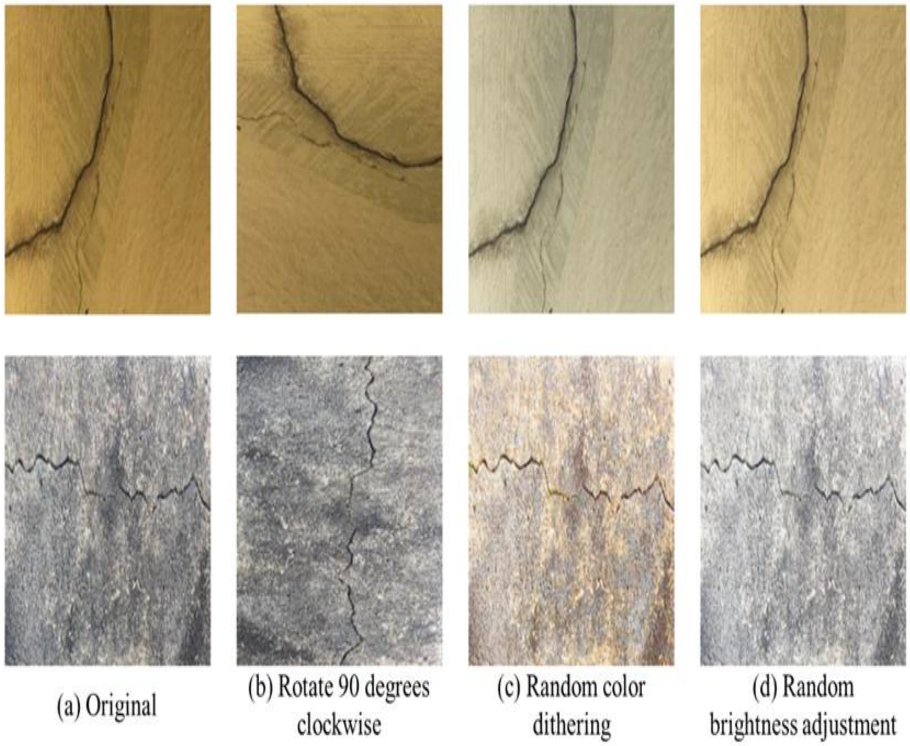


Fig. 13. Image enhancement processing diagram.

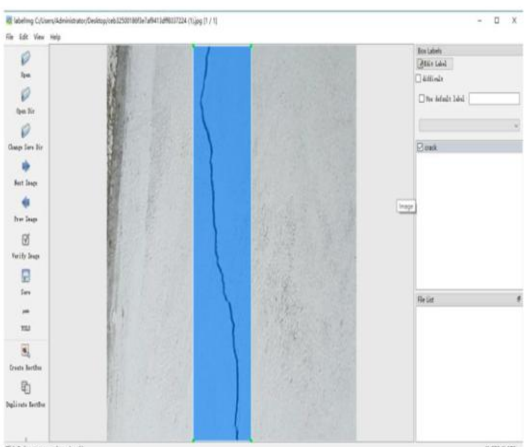


Fig. 14. Crack image annotation interface.

Fig. 15. Structure of crack image annotation labels.

B. *Experimental Environment and Training Parameter Settings*

In order to match the computational complexity of the algorithm, this paper configures the experimental environment as shown in Table I.

TABLE I. EXPERIMENTAL ENVIRONMENT SETTINGS

Environment Configuration	Parameterisation
CPU	AMD Ryzen7 5800H
RAM	16GB
GPUs	RTX 3060 Laptop
memory	6GB
fig. pattern	Pytorch

The parameter settings of the depth algorithm used in this paper are shown in Table II.

TABLE II. PARAMETER SETTINGS OF DEEP ALGORITHM

Parameter name	Parameterisation
Batch_size	2
epoch	156
optimisation algorithm	AdamW
learning rate	0.00285
Input image resolution	640 x 640

C. Evaluation Indicators

In order to effectively evaluate the effectiveness of the algorithm in this paper, the check accuracy rate (Precision), the check full rate (Recall) and the mean average precision (mean Average Precision, mAP) are used as the evaluation indexes, and the specific calculation formula is as follows:

$$P = \frac{TP}{TP + FP} \tag{2}$$

$$R = \frac{TP}{TP + FN} \tag{3}$$

$$mAP = \frac{\sum_{i=l}^{C} AP_i}{C} \tag{4}$$

where P is the checking accuracy rate; R is the checking completeness rate; mAP is the Average Precision (AP) of the mean; TP denotes the true category, i.e., the model correctly predicts the positive category samples to be positive; FP denotes the pseudo-positive category, i.e., the model incorrectly predicts the negative category samples to be positive; FN denotes the pseudo-negative category, i.e., the model incorrectly predicts the positive category samples to be negative; AP_i denotes the Average Precision (AP) value for the i-th category; and C denotes the total number of categories.

D. Analysis of Experimental Results

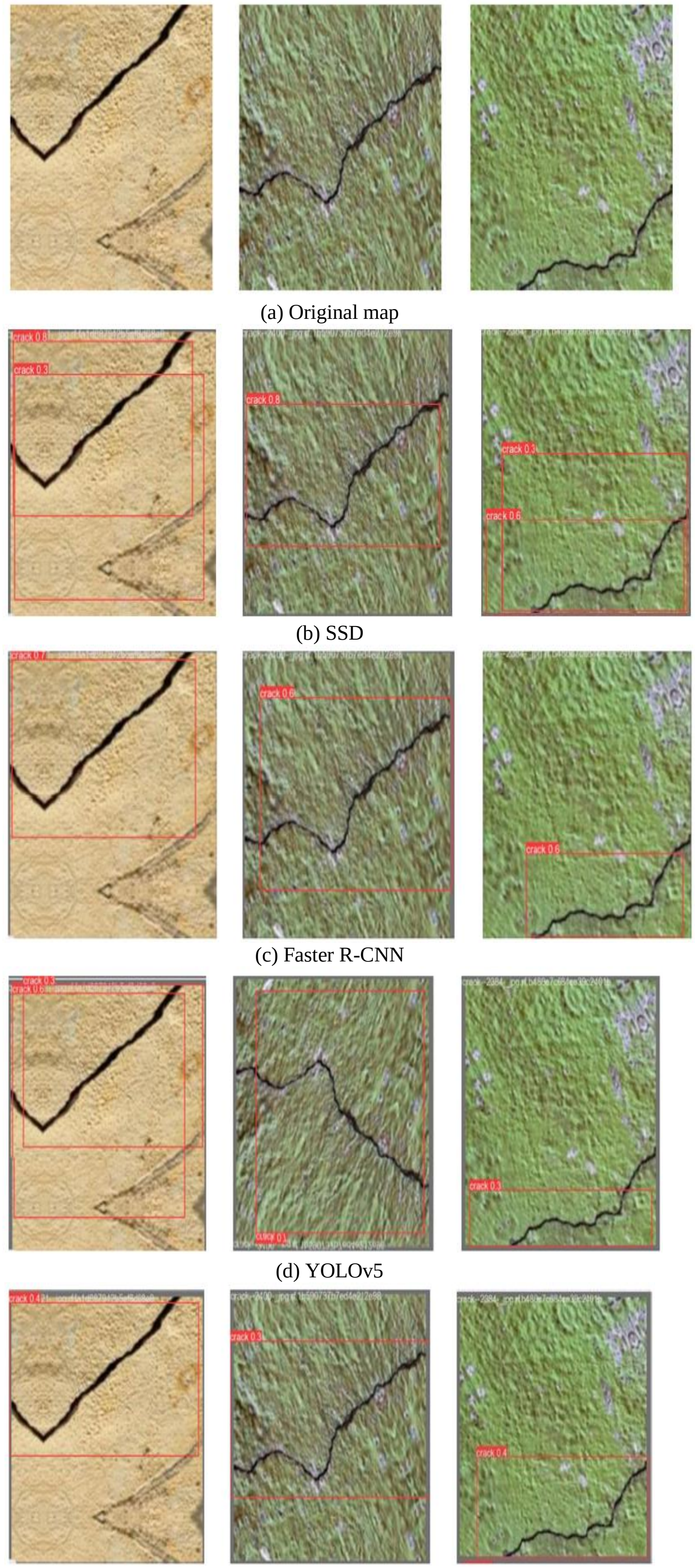
1) Analysis of concrete crack detection results: In order to verify the effectiveness of the concrete crack detection algorithm proposed in this paper, SSD [26], Faster R-CNN [27], and YOLOv5 [28] are used in this paper to conduct comparative experiments with Mask R-CNN, and the results of the experiments are shown in Table III and Fig. 16.

As can be seen from Table III, the concrete crack detection model Mask R-CNN proposed in this paper has a high detection accuracy, with mAP reaching 94.9%, Precision reaching 90.5% and Recall reaching 89.5%.

TABLE III. EXPERIMENTAL RESULTS OF DIFFERENT DETECTION MODELS

Arithmetic	mAP	Precision	Recall
SSD	0.876	0.832	0.748
Faster R-CNN	0.933	0.885	0.855
YOLOv5	0.928	0.879	0.851
Mask R-CNN	0.949	0.905	0.895

From Fig. 16, it can be seen that SSD, Faster R-CNN and YOLOv5 models have duplicated detection frames and low detection completeness, and the Mask R-CNN model proposed in this paper has a better performance in the localisation and identification of cracks compared to the target detection model, especially in the crack detection completeness, which is better than the other models and can satisfy the daily crack detection in concrete bridges. The Mask R-CNN model proposed in this paper.



(a) Original map
(b) SSD
(c) Faster R-CNN
(d) YOLOv5
(e) Mask R-CNN

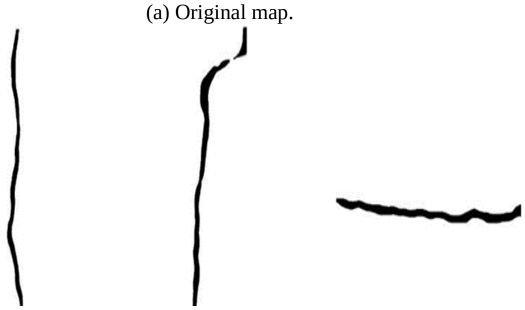
Fig. 16. Comparison of detection results.

2) Analysis of concrete crack segmentation results: In order to verify the effectiveness of the bridge crack profile segmentation algorithm proposed in this paper, U-Net [29], Mask R-CNN, and YOLOv5-seg [30] are used in this paper to conduct comparative experiments with DeepLabV3+, and the results of the experiments are shown in Table IV and Fig. 17. From Table IV, it can be seen that the DeepLabV3+ model has the highest segmentation effect accuracy compared with other segmentation models, with mAP, Precision, and Recall reaching 48.9%, 67.4%, and 56.7%, respectively. From the segmentation effect diagram (Fig. 17), it can be seen that the bridge crack detection model proposed in this paper achieves better results in the evaluation indexes. In order to more intuitively show the effect performance of different models in bridge crack contour extraction, the same bridge crack image is segmented by using different models, and the results of contour extraction verify that the algorithms proposed in this paper have high accuracy and completeness of contour extraction.

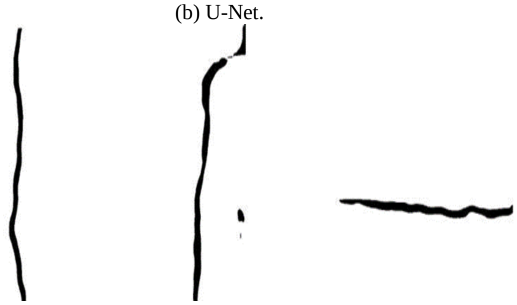
TABLE IV. EXPERIMENTAL RESULTS OF DIFFERENT CRACK SEGMENTATION MODELS FOR CONCRETE STRUCTURES

Arithmetic	mAP	Precision	Recall
U-Net	0.466	0.616	0.503
Mask R-CNN	0.476	0.643	0.520
YOLOv5-seg	0.485	0.637	0.528
DeepLabV3+	0.489	0.674	0.567

(a) Original map.

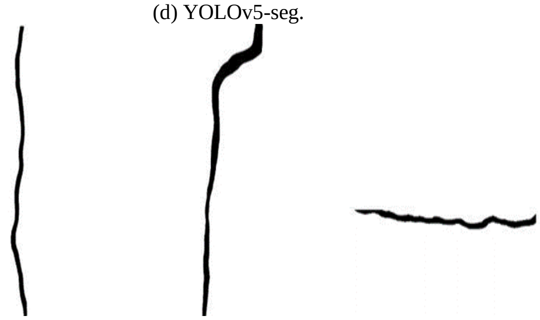


(b) U-Net.



(c) Mask R-CNN.

(d) YOLOv5-seg.



(e) DeepLabV3+.

Fig. 17. Comparison of segmentation results.

V. CONCLUSION AND OUTLOOK

Aiming at the current concrete structural crack detection and segmentation methods, which have problems such as low recognition ability and inaccurate extraction of the contour of cracks, this paper fuses DeepLabV3+ and Mask R-CNN algorithms, and proposes a concrete structural crack detection and segmentation method based on DeepLabV3+ and Mask R-CNN algorithms. A concrete structure crack detection and segmentation method based on DeepLabV3+ and Mask R-CNN model is proposed by analysing the problem of concrete structure crack detection and segmentation, designing a solution method, and combining DeepLabV3+ and Mask R-CNN algorithm. Using the bridge crack image data for validation and analysis, the Mask R-CNN model has a better performance in the localisation and identification of cracks compared to the target detection model, especially in the integrity of crack detection than other models; the bridge crack detection model achieves better results in the evaluation indexes, and has a high accuracy and integrity of contour extraction in the task of crack contour extraction for concrete bridges. The next step is to improve the training speed of DeepLabV3+ and Mask R-CNN algorithms, and further validate the effectiveness of the algorithms from crack detection problems in different fields.

The proposed method effectively solves key issues in crack detection, especially in locating fine cracks and achieving better segmentation. Despite the strong performance, we note two primary limitations: 1), The current implementation requires significant computational resources, and the training process is slow. 2), Although tested on bridge crack data, the method's performance in other types of concrete structures or environmental conditions has not yet been fully validated.

Prospects for future research directions through this study can be focused on the following aspects: Firstly, Future research could focus on optimizing the training process to make the models faster and more efficient without sacrificing accuracy. Secondly, Additional studies are needed to test the method on more diverse datasets and environments to ensure the model's robustness across different types of concrete structures. Finally, investigating the use of lightweight neural networks could reduce the computational load and make real-time crack detection more feasible. These future directions aim to further enhance the method's practical applicability and broaden its use in various civil engineering contexts.

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