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Research on Computer Classification Algorithm of Concrete Crack Based on Deep Learning

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Abstract: - In combination with transfer learning under the framework of Unet semantic partitioning, VGG16 pre-trained neural network enhanced encoder is used to extract multi-level high-level semantic information. The cross-entropy loss function is used to eliminate the imbalance between samples, and finally the crack shape is accurately semitone. Combining with the theory of computer vision, a quantitative calculation method of the crack region, length, width and other geometric characteristic parameters based on the binary segmentation template is proposed. Finally, the self-developed dam concrete crack image is taken as an example to carry out simulation and comparison test to check the correctness and superiority of the research results of this project. The research results will reveal that the crack recognition based on deep neural network can achieve a high recognition rate. The calculation results of fracture characteristic parameters meet the requirement of detection accuracy. The research results of this paper are expected to provide a new technical means for the quality control of dam concrete structure.

Keywords: Dam Concrete; Crack Detection; Semantic Segmentation; Feature Quantization; Deep Learning.

I. INTRODUCTION

Under the influence of environmental erosion, internal chemical reaction and load, concrete dam is very likely to have diseases. Dam cracking is the most common disease of dam, the direct cause of which is the damage of dam structure, which seriously reduces the durability, strength and stability of dam. Most cracks occur in the surface of buildings, which is a common disease [1]. The cracking of concrete dam not only endangers the normal operation of the dam, but also may lead to other damage such as concrete spalling, leakage and freeze-thaw damage on the dam surface, and even cause operational safety problems [2]. Therefore, real-time monitoring of cracks in concrete dam can prevent further damage of concrete dam. At present, the dam disease monitoring is mostly carried out by hanging basket on the dam surface or by visual observation [3]. The existing detection methods cannot detect the dam in real time, which causes the dam to delay the maintenance time, and the detection cost is high and the risk is high. Driven by advanced technologies such as drones and deep learning, some studies first use drones and underwater robots to obtain dam images, and then use machine vision technology to diagnose dam damage. Some scholars have applied deep convolutional neural networks to crack identification of concrete DAMS. Some researchers have improved FCN to improve the accuracy of crack identification in dam panels. Some scholars have perfected U-type full convolutional neural network (U-net) and applied it to existing hydraulic concrete crack samples, and obtained good results [4]. The above research can effectively segment the cracks in the image, but it has the disadvantages of long operation time and poor real-time performance. In addition, due to the poor service condition of the reservoir, the background of the crack image is complicated, and the characteristics of the crack image are fuzzy, which increases the difficulty of identification [5].

In recent years, researchers at home and abroad have introduced Faster R-CNN into the detection and localization of complex structures. Some researchers have organically integrated object detection with smart phones to study a new type of damage identification method for brick-concrete structures. A structural model based on Faster R-CNN has been proposed, which can identify and locate various forms of damage after structural failure [6]. At present, a multi-objective crack recognition method based on deep convolutional neural network has been established, which can achieve accurate recognition, segmentation and statistics of cracks. The above research shows that target detection algorithm has been widely used in tunnel, road and house construction projects, but there is still a lack of research on target detection algorithm to identify visible cracks in concrete DAMS online. In this paper, YOLOX neural network is used to develop a new algorithm for dam crack online monitoring [7]. The deep convolution attention mechanism is introduced to enhance the emphasis on crack characteristics and improve the detection ability of crack characteristics, and the perfect concurrency loss function is introduced to improve the detection accuracy of crack defects.

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II. SHAPE DIVISION AND QUANTITATIVE CHARACTERIZATION OF CRACKS IN DAM BODY

A. *U-shaped network pattern architecture*

The Unet mode is a perfectly symmetric coding-decoding system, with the encoder on the left consisting of multiple convolution and pooling operations with drop sampling as the core [8]. The decoder on the right maps features to the original image size by up-sampling adjustment and predicts the category markers for each pixel. A descending layer structure based on the maximum pool is proposed, which consists of four sub-stages. The resolution of the first to fifth components is 572x572, while the resolution of the first to fifth components is 572×572,284×284,140×140,68×68,32×32. Since the above convolution all uses valid mode, the resolution of the latter submodule $R_{i+1}=(R_i-4)/2$, where R_i is the resolution of the former submodule [9]. The decoder consists of four sub-blocks, and the resolution of the feature map is successively increased by up-sampling until it is consistent with the resolution of the input image. A jump-based method is proposed to fuse the sampled data with the data of other subcomponents of the same resolution, and then use it for the next decoding. In general, Net-net can combine the low resolution of down sampling, high resolution of up sampling and high-level semantic information of jump connection, and has a wide application prospect in small-scale image segmentation [10]. A schematic diagram of the U-net model architecture is shown in Figure 1 (image cited in Entropy 2023, 25(7), 1085).

$$\begin{cases} E(u)=\sum_{u\in\Omega}\omega(u)\lg(\eta_c(u)) \\ \omega(u)=\omega_z(u)+\omega_0\cdot\exp((d_1(u)+d_2(u))^2/(-2\sigma^2)) \end{cases} \tag{1}$$

u is the pixel point. The space Ω is a subset of the set of integers. c is the category label of the pixel. η is the output value of the activation function of the pixel in the corresponding category. ω is the boundary weight. ω_z is the weight used to balance the class frequency. d_1, d_2 is the Euclidean distance from the current pixel point to the boundary of the nearest and the next nearest object. ω_0, σ is an adjustable parameter.

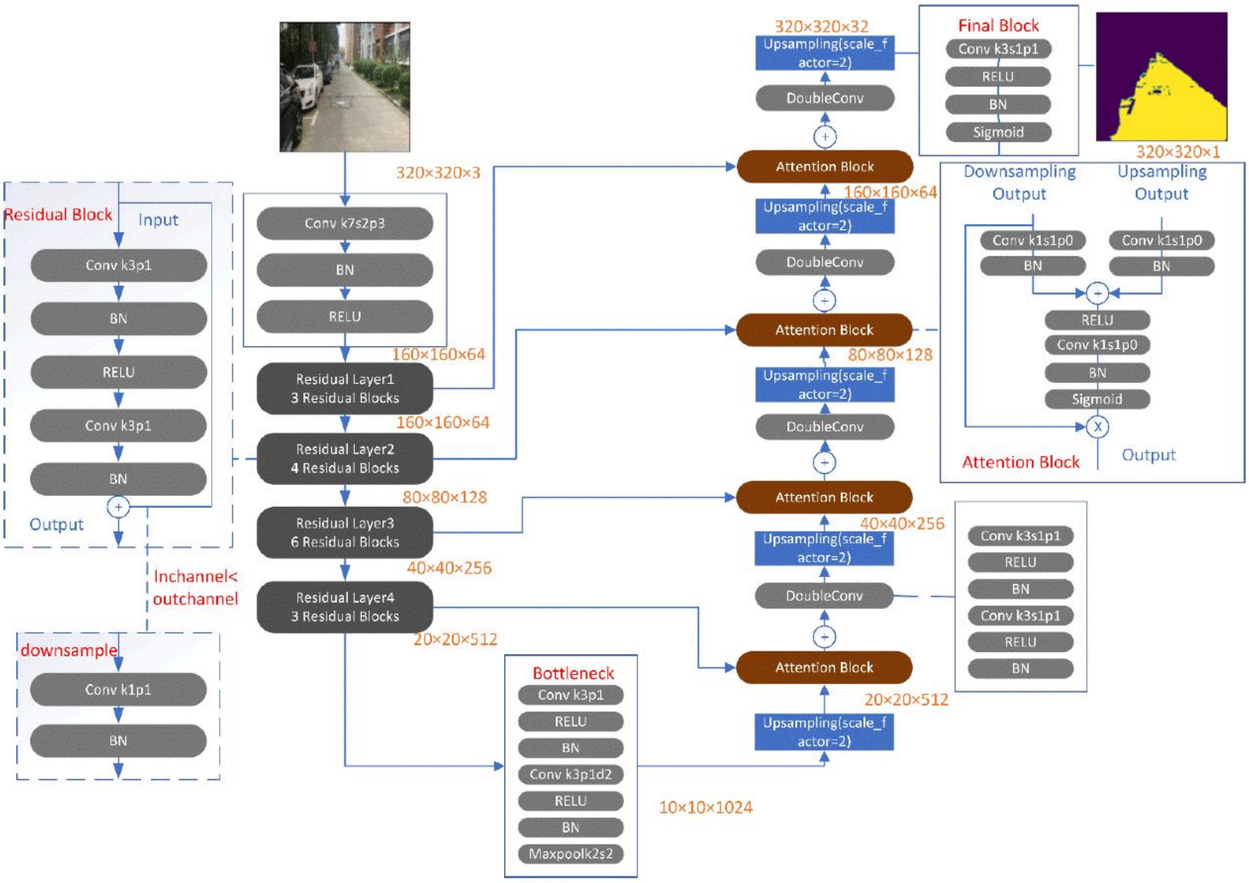


Fig.1 Schematic diagram of U-net model architecture

B. U-net model improvement strategy

Different from biomedical objects such as cells, concrete cracks have their own characteristics in structure, and it is necessary to further improve the U-net structure to meet the requirements of crack identification [11]. Since the shape, direction, size and distribution of each crack are not the same, coupled with the influence of external conditions such as external lighting, how to accurately obtain the deep internal characteristics of the crack is an important link to realize the fine division of the crack. However, the encoder of the left wing of the original U-net model has great limitations, resulting in the effective characterization of the crack [12]. And a large number of negative samples are easy to identify, resulting in the failure of U-net model. Therefore, this project intends to study the optimization strategy for U-net optimization from two perspectives of network structure and loss function.

III. REINFORCEMENT ENCODER FOR NEURAL PRE-TRAINING BASED ON VGG16

Deep neural network has some problems, such as the increase of parameters to be learned, the increase of computation, and the slow convergence speed. In this project, a new migration algorithm is proposed, which takes ImageNet as an example to construct a pre-processing model with shared features to initialize the network weights. Among them, VGG16 is a deep convolutional neural network developed by a team at the University of Oxford, which consists of 13 convolutional networks, 3 layers are fully connected, and each layer adopts 3x3 convolutional kernel convolution and combines it into a convolutional sequence [13]. After the convolutional neural network is convolved, the modified linear element is used to realize the maximum pool of the convolution of each layer, so as to realize the effective fusion of the convolution of each layer. The VGG16 network architecture is shown in Figure 2 (image cited in Accelerating Deep Neural Networks on Low Power Heterogeneous Architectures).

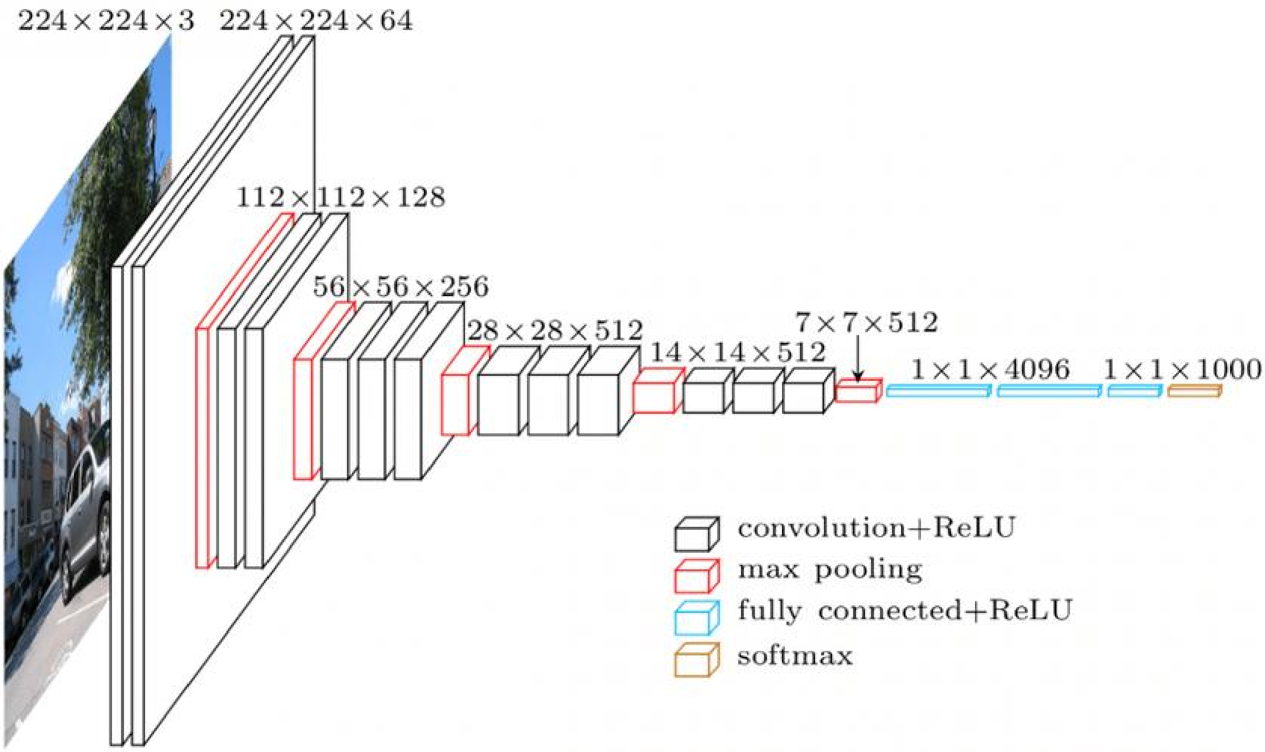


Fig. 2 VGG16 network structure diagram

A deep neural network based on VGG16 is proposed to replace the encoder in U-net mode. VGG16 combines the multi-scale characteristics of image with decoding algorithm[14]. It should be noted that the input to the VGG16 network is a multi-layer image with a resolution of 224x224 pixels, rather than a black and white image, and the encoded image size is only one-sixteenth of the original image.

A. Improved binary cross entropy loss function

An image classification method based on mutual entropy method is proposed, that is, the difference between each pixel in the image is used to classify the image [15]. The loss function of traditional U-net mainly focuses on the boundary of the target, and does not take into account that the learning of the model is easily affected by a lot of negative sampling. The damage function is used to weight different types of samples to improve their ability to identify complex cracks. Therefore, this project intends to realize effective regulation of the weights between positive and negative samples by cooperating with FocalLoss, two kinds of cross-entropy loss functions. The formula for calculating FocalLoss is:

$$G(u)=\begin{cases}-\lambda(1-\eta_c(u))^{\gamma}\lg(\eta_c(u)), v_c=1\\ -(1-\lambda)\eta_c^{\gamma}(u)\lg(1-\eta_c(u)), v_c=0\end{cases} \tag{2}$$

λ is the positive and negative sample adjustment coefficient. γ Easily distinguishable sample adjustment coefficient. v_c is a real sample label [16]. All λ,γ are dynamic scaling factors, and the method of manual adjustment can effectively improve the loss weight of positive samples and reduce the loss weight of high set confidence. A new method for crack shape division of dam concrete based on U-net structure is proposed.

B. Solution of fracture characteristic parameters

It is very important to quantitatively describe the crack characteristics of the dam concrete structure to improve the safety of the dam concrete structure [17]. At present, the automatic extraction of fracture region, length, width and other geometric characteristics is realized based on the results of EU-net fracture division.

a. Image Preprocessing

First, use morphological erosion and expansion technology to eliminate noise such as discrete points in the image; then, through connected area operation, discontinuous crack blocks are spliced.

$$g-\varepsilon=\{u,v\,|\,(\varepsilon)_{uv}\subseteq g\} \tag{3}$$

$$g+\varepsilon=\{u,v\,|\,(\varepsilon)_{uv}\cap g\neq\varnothing\} \tag{4}$$

g is a set of image pixels to be processed. ε is a structural element. (u,v) is the position coordinate of any pixel point on the set g.

b. Calculation of crack length and width

A crack feature extraction method based on local encryption is proposed, and the full length C_z of the crack is calculated using the piecewise summation method [18]. The following formula can be used to convert and obtain a characteristic parameter that characterizes the overall mechanical properties of the crack. The average width of the crack is expressed as $\overline{E}_z$:

$$\overline{E}_z=R_z/C_z \tag{5}$$

c. Calculation of the maximum seam width

The maximum crack width of the dam body should be within the requirements of the design specification, so it is necessary to determine the maximum crack width accurately. Firstly, the maximum crack width in the single connected region is obtained by solving the distance between the upper- and lower-pixel points [19].

$$\begin{cases}E_z^i=\min(\sqrt{(u_i-u_j)^2+(v_i-v_j)^2})\\ E_{\max}=\max(E_z^i)\end{cases} \tag{6}$$

$(u_{i,j},v_{i,j})$ is the position coordinates of each pixel on the upper and lower boundaries respectively.

IV. Experimental verification

A. Construction of experimental data set

In this paper, PagonM300RTK and Canon EOS80D cameras were used to observe several DAMS in Liaoning Province, and the image data of dam cracking were obtained. In the range of 3-20 meters, the picture is taken in low light [20]. The project planned to cut and screen the collected dam crack images, establish a test database and obtain 940 images (640x640) containing crack damage (Figure 3 is quoted in).

Fig. 3 Example of crack image acquisition for concrete dam

Firstly, the robustness of YOLOX-DCD algorithm is improved by means of color gamut adjustment, noise addition, level flip, brightness adjustment, rotation, etc. After manual screening, the number of samples was eventually expanded to 1600, and the results were shown in Figure 4. Secondly, LabelImg labeling software was used to mark the cracks, and the tags in PASCALVOC format were obtained and saved in XML document form. The result was 1280 samples, 160 validation samples, and 160 test samples.

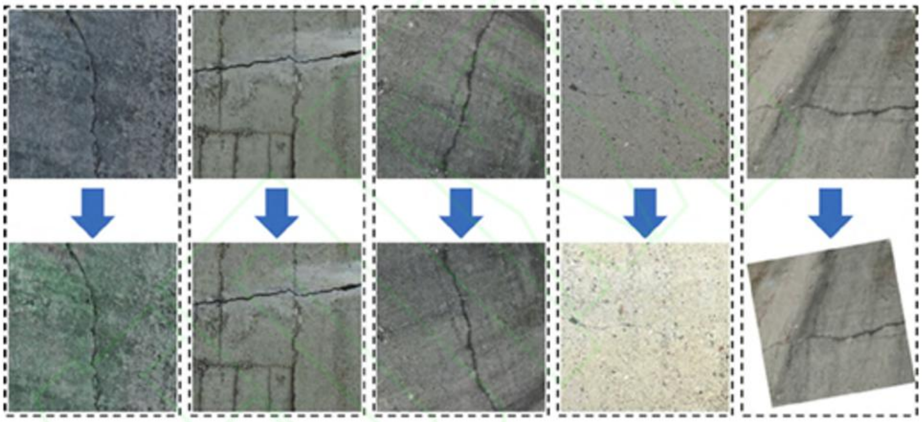


Fig.4 Data enhancement image

B. Experimental Platform

This test was performed on a workstation equipped with an Intel i9-10850K CPU and a NVIDIA2080Ti graphics card. In order to ensure the best learning results during the training, we set up 200 cycles. The first 150 rounds used Mosaic, MixUp and other strengthening algorithms, and the last 50 rounds were stopped. This paper uses a stochastic gradient-based approach where the momentum term is set to 0.9 and the weighted reduction rate is 0.0005. Set the batch size to 8 based on the memory size of the video card.

C. Results

Figure 5 shows the change in losses throughout the network mode training process. As can be seen from Figure 5, the overall loss decreases rapidly during the initial training session. Then the overall loss will slowly decrease, and then it will stabilize. When learning the 150th round, through the learning of Mosaic and Mixup algorithms, the overall performance of the system has been greatly reduced, and good consistency has been maintained in each cycle.

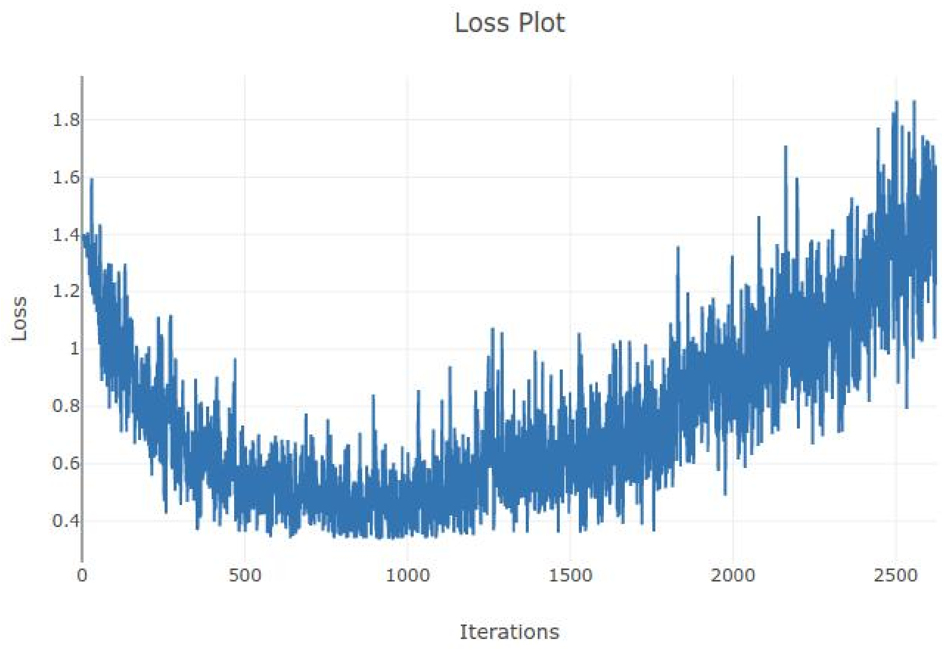


Fig.5 Overall loss changes during network training

a. Ablation experiment

The validity of the model is tested by constructing the dam fracture database and using YOLOX-m as the standard neural network. The results of ablation experiments are shown in Table 1.

Table 1 Results of ablation experiment

experiment	CIoU	SE	ECA	CBAM	AP0.5/%	P/%	FPS/($f\cdot s^{-1}$)	Model size /MB
1	-	-	-	-	92.69	90.43	73	26.33
2	√	-	-	-	93.24	92.70	73	26.33
3	-	-	-	√	93.98	92.49	67	26.74
4	√	√	-	-	93.46	93.24	72	26.53
5	√	-	√	-	94.07	92.21	73	26.33
6	√	-	-	√	94.63	92.81	68	26.74

In Table 1, test 1 is the measured data of the standard network, test 2 and 3 are the effect after optimization of the standard network, and test 4-6 is the effect of adding SE, ECA and CBAM into the network on the performance of the entire system. Both CIoU loss function and CBAM algorithm can effectively improve the detection performance of the network. In test 2, due to the addition of CIoU loss function, AP0.5 and P are greatly improved without any influence on the detection rate and model size. In experiment 3, by embedding CBAM model into the network, AP0.5 and P increased by 1.24% and 1.98% respectively, which enhanced the degree of attention to cracks and thus enhanced the recognition of cracks. Experiments 4-6 show that the attention mechanism can improve the degree of attention to the crack characteristics and suppress the influence of other contexts [21]. After the addition of CBAM, the overall performance of the whole network increases most obviously, AP0.5 and P are 1.86% and 2.29%, respectively, which also indicates that paying attention to the fracture characteristics in channel and space can improve the performance of the network. The algorithm in this paper (experiment 6) guarantees the accuracy of the algorithm on the premise of fast detection.

b. Network Performance Comparison of multiple target detection

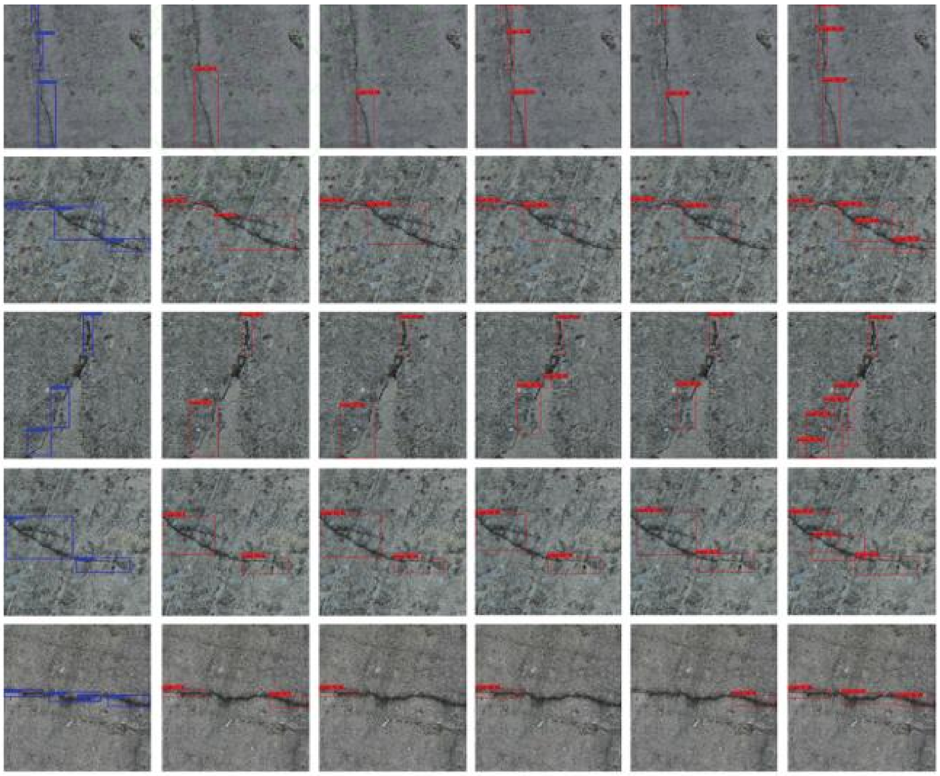
By comparing with FasterR-CNN, SSD,YOLOv3,YOLOv4, and standard YOLOX-m network, the correctness and advantages of YOLOX-DCD algorithm are proved. Through the study of the above network, the loss function converges and the network performance reaches the optimum, and then the performance of the network is tested. The experimental data of other types of neural networks and YOLOX-DCD are shown in Table 2. Among them, the YOLOX-DCD neural network is only 25.67M, which has a high accuracy rate. APR0.5 reaches 90.84%, FPS is 65. The detection performance of YOLOX-DCD has decreased, but its performance has improved compared with the traditional visual perception method, its performance index has increased by 1.86%, and F1, P and R have been well improved. The YOLOX-DCD model is slightly larger than SSD, and other performance is better than SSD, indicating that YOLOX-DCD has higher speed and performance than SSD.

Compared with traditional fast convolutional neural networks, YOLOv3 and YOLOv4, YOLOX-DCD has higher detection accuracy speed.

Table 2 Test results of other target detection neural networks and YOLOX-DCD

network class	Model size /MB	AP0.5/%	F1/%	P/%	R/%	FPS/($f \cdot s^{-1}$)
FasterR-CNN	142.39	85.94	65.72	50.88	92.78	32
SSD	24.59	85.49	76.81	92.30	65.77	48
YOLOv3	64.53	90.94	87.32	85.58	89.14	50
YOLOv4	67.04	90.68	85.08	92.69	78.64	59
YOLOX-m	26.33	92.69	88.72	90.43	87.08	73
YOLOX-DCD	26.74	94.63	91.40	92.81	90.02	68

The image was identified using a trained multi-object detection neural network, in which the detection box in YLOXDCD was set to blue, while the other networks were set to red. From Figure 6, YOLOX-DCD detected all the cracks in test figures 1 to 5, and the detection frame covered the crack area completely, while the detection results of the other 5 networks were not accurate. Among the other 5 kinds of imprecise network detection, YOLOX-m,YOLOv4,YOLOv3, SSD, etc. all have erroneous detection, resulting in low detection efficiency. In addition to FasterR-CNN, the detection boxes of other methods failed to achieve complete coverage of the fracture region, and although FasterR-CNN could detect all the cracks, the identification accuracy was not high due to a large number of overlaps. Compared with traditional neural networks, YOLOX-DCD has better ability to recognize visual crack images.



(b) YOLOX-DCD (c) YOLOX-m (d) YOLOv4 (e) YOLOv3 (f) SSD (g) Faster R-CNN

Fig.6 Detection results of multi-target detection neural network on test set

c. Detection effect in different lighting environments

Under the influence of the uneven sunshine and the block of the bridge pier, the shadow is easily produced on the overlying dam surface, resulting in the inconsistency of image brightness and shadow block. Under bright lighting conditions, the characteristics of cracks are clearer and easier to identify because of good lighting conditions [22]. In the case of poor illumination, poor illumination, large surface fluctuation and large background noise, it is more difficult to identify cracks. YOLOX-DCD was used to detect the crack in the image with shadow, and a good result was obtained. As can be seen from FIG. 7 the proposed algorithm can well identify crack images under various lighting conditions, indicating that the proposed algorithm is effective and robust for crack detection under various lighting conditions.

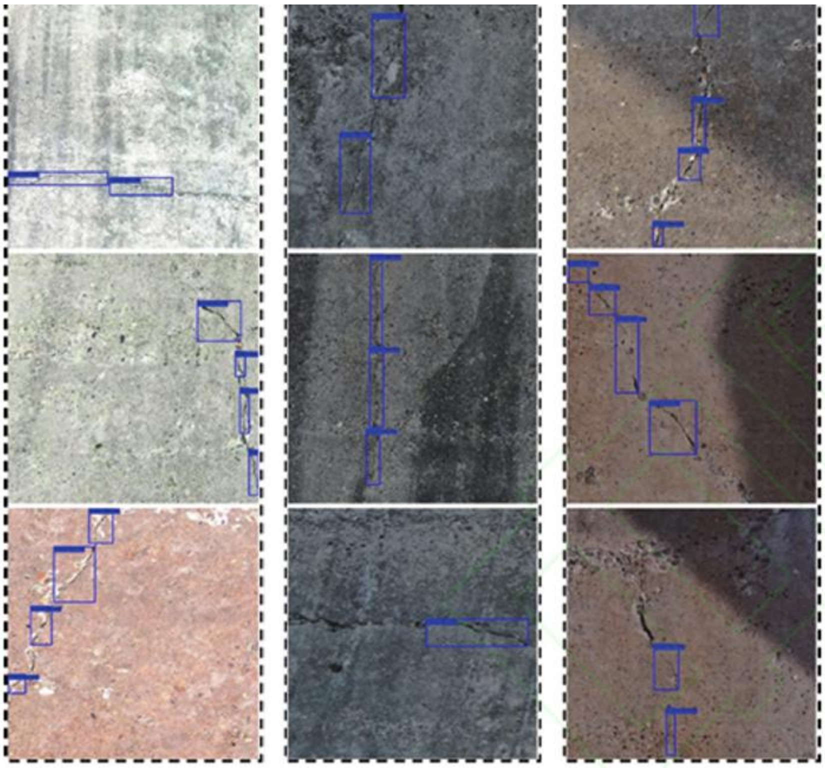


Fig.7 Crack image detection results under different lighting environments

d. High-resolution image detection effect

The sample used in this paper is 640x640 small size image, which has obtained a good recognition effect in the test. However, since the images obtained by the UAV/digital camera are high-precision image. The paper imported the 5184x3888 high-resolution images into the artificial neural network for detection, and the detection effect obtained is shown in Figure 8. This method has achieved good results and can effectively detect cracks. This problem can be solved by shortening the shooting distance or changing the focal length of the lens to enhance the features of cracks in the image.

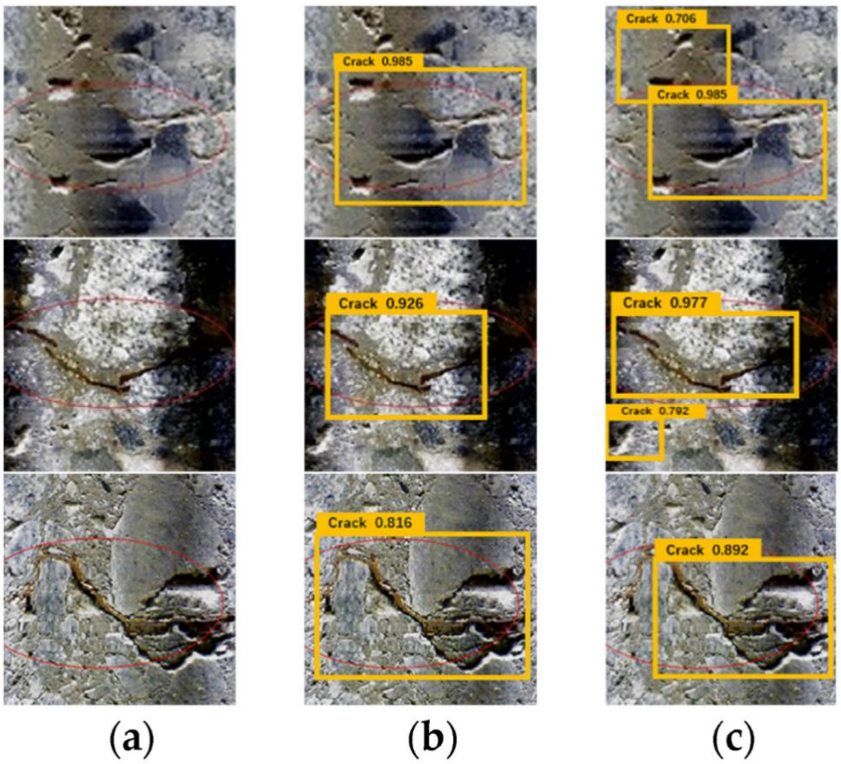


Fig.8 High-resolution image detection results

V. Discussion

The damage monitoring of the dam body can detect the potential potential defects and other abnormal states in time, so as to find the root cause of the problems, so as to prevent the occurrence of major projects and ensure the safe operation of the dam body. For Longhekou Reservoir in Yunnan province, manual observation was used in the past, such as using hanging baskets and setting up supports. With the progress of science and technology, there are many non-contact crack detection techniques. Optical fiber sensing technology is used more and more in dam safety monitoring because of its high sensitivity, high precision and easy construction. It is necessary to set up some sensors in the dam body, such as the temperature crack of the Three Gorges reservoir to detect the temperature, stress and other changes in the dam body. However, due to the factors such as the type and arrangement of the optical fiber sensor used, the measurement results are greatly affected, resulting in its application in the dam crack identification is still in the stage of theoretical and experimental research. Vision is the source of human and biological cognition and understanding of external things. Data show that 80%-90% of the information people get from nature comes from vision, and vision plays an important role in daily life. But if you have vision, it can sense the environment like humans do, and thus replace humans to do those dangerous things. Computer vision is a new technical topic emerging in recent years. In recent years, it has a broad application prospect in many aspects such as machine vision research, aerial mapping, military, medical imaging and engineering inspection. Binocular vision technology has the characteristics of high efficiency, high precision, simple operation and low cost, and is increasingly used in field non-contact product monitoring and testing. In water conservancy and hydropower projects, ensuring the safety of the dam body is always the most important problem, and the detection and monitoring of the crack of the dam body is a very important link. Among them, deep learning and machine vision inspection are hot research areas in recent years. The combination of deep learning and binocular vision is of great theoretical and practical significance in the crack identification and detection of dam body. With low cost and high precision, this technology can monitor the dam more accurately and improve the safety of the dam. The correction method based on YOLOV5S-Ghost is adopted to detect and identify the crack of the dam body, and the crack of the dam body is accurately located by using camera calibration, stereo matching and other methods, so as to detect and detect the crack of the dam body. This project intends to integrate deep learning with binocular vision technology and apply it to crack detection and monitoring of dam body. Although some research results have been obtained, there are still many defects due to factors such as instruments and conditions, which need to be further improved. Its core contents are as follows:

1) Choose a dual-lens camera. Choose the correct camera resolution: Higher camera resolution can provide more accurate measurement results. However, due to the use of high-resolution cameras, the processing process of the system is very slow, so we must choose the appropriate resolution for different applications. Choose the right camera: Each camera has its own advantages and disadvantages when testing. For example, CCD cameras are suitable for dark environments, while CMOS cameras have higher frame rates and lower energy consumption.

2) Camera calibration problem. At the same time, due to the use of more accurate calibration template and the corresponding calculation method, the calibration of multiple measuring points is realized as far as possible, so as to reduce the measurement error. More accurate correction algorithm and more image data should be used in correction. A more accurate feature extraction and matching method is adopted in this method, and the recognition rate is improved by repeated matching.

3) The crack boundary of the dam body is divided optimally. 1. Using high-definition image acquisition: Using high-resolution image acquisition devices to improve image sharpness and accuracy, and to accurately capture the fault. 2. According to different environments, appropriate boundary detection methods are selected and optimized. By adjusting algorithm parameters and selecting different filters, the deep learning model is used to enhance the accuracy and robustness of image boundary detection.

4) Optimize the identification of cracks in the dam body. By using high precision instrument, the accuracy and accuracy of test results can be effectively improved, and the occurrence of wrong judgment and wrong judgment can be reduced. 2. In view of the existing micro-cracks, a new micro-crack identification method based on wavelet transform is proposed and improved, so that cracks can be found and dealt with in a relatively short time. When using the deep model for learning, it is necessary to collect sufficient marker samples and carry out quality management to improve its promotion performance.

VI. Conclusion

This project takes the surface crack of concrete dam as the research object, and establishes the online crack identification algorithm YOLOX-DCD based on object recognition. Finally, the dam crack image database is constructed by using the real crack images collected by UAV and digital camera, and the theory and algorithm proposed in this project are verified. Experiments show that the method is fast, accurate and real-time. The experiment is compared with the existing multi-object detection neural network. Compared with the existing object detection neural networks, the AP0.5 and F1 of the proposed algorithm reach 90.84% and 87.74%, respectively, with higher accuracy. Since the FPS is 65, the detection time is relatively short. With a volume of 25.67 MB, the method has a small volume and can achieve real-time detection of cracks on a mobile phone. Experiments show that YOLOX-DCD has good adaptability and robustness to crack images under various illumination conditions. The effectiveness of the method is verified by the analysis of high precision crack image.

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