Damage Security Intelligent Identification of Wharf Concrete Structures under Deep Learning and Digital Image Technology

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***Abstract*—Artificial Intelligence (AI) technology has quickly developed under the mighty computing power of computers. At this stage, there are many mature non-destructive testing methods in civil engineering, but they are generally only suitable for simple structures and evident damage characteristics. Therefore, it's necessary for us to investigate the damage identification of wharf concrete structures under deep learning and digital image technology. The article propose a damage detection and localization method based on Neural Network (NN) technology in deep learning and Digital Image Correlation (DIC) to identify internal damage to concrete used for wharf construction. Firstly, the identification model of concrete structure is constructed using NN technology. Then, structural damage identification of concrete is further investigated using DIC. Finally, relevant experiments are designed to verify the effect of the model. The results show that: (1) The damage model of concrete structure constructed by NN technology has high convergence and stability and can control the test error well. (2) The image output by the DIC equipment is processed and input into the NN. The errors of the various parameters of different concretes can be within the acceptable range. This paper aims to provide good ideas and references for follow-up structural health monitoring and other topics and has significant engineering application value.**

Keywords*—*Structural damage identification; deep learning; neural network; digital image; concrete

I. Introduction

In recent years, deep learning and artificial intelligence have developed rapidly. Structural damage identification methods based on AI are gradually applied in practical engineering. In AI, domestic and foreign experts and scholars generally focus on techniques such as the Genetic Algorithm (GA), wavelet analysis, and Neural Networks (NNs) [1]. Zhang and Zhang used GA to locate and quantify the degree of damage and proposed a new form of genetic search optimization objective function. They proved that the method could effectively identify the damage location and degree of an elastic structure through the numerical simulation analysis of the visible structural damage of a flexible structure based on the modal analysis theory [2]. Huang et al. proposed a damage identification method based on GA. The method combined the modal flexibility matrix to identify the structural damage to the shear wall. The results showed that the method could identify damage under insufficient dynamic data through experimental analysis and numerical simulation [3]. Li et al. proposed a damage identification method based on GA and the damage structure model. For the cracked cantilever beam structure, the optimization calculation of binary and continuous GA was used to prove that this method accurately identified the structure's damage location and degree [4].

Scholars proposed the Digital Image Correlation (DIC) at South Carolina State University in 1981. Scholars calculated the surface displacement of the sample by converting the ultrasound information into a two-dimensional digital ultrasound image. After comparison, the image strain of the sample could be obtained and used to measure the average thickness of the material [5]. Later, it was found that a fast Fourier transform could be used to obtain the corresponding local displacement data caused by the displacement change of the sub-region by dividing the two speckle images. It could be successfully applied to studying the deformation field at the crack tip, developing this method [6]. At present, in the field of civil engineering, the DIC measurement method is mainly applicable in two directions: one is to observe the crack propagation and deformation status of reinforced concrete components in real-time, and the other is to observe the strain and displacement fields on the surface of reinforced concrete components after deformation in real-time. Now certain research results have been achieved in both aspects. Molina Viedema et al. used a frame structure as the research object and extracted the working modes of the structure under random vibration excitation using the three-dimensional dynamic displacement field provided by DIC method. Local mode filtering method was used to identify and locate the damage of the frame beam, achieving high positioning accuracy [7]. Kleinendorst used DIC measurement technology to study the stiffness damage identification of reinforced concrete beams, and compared it with the measured values of deflection displacement and the results of finite element modeling of beams at various stages. He concluded that DIC measurement error is very small and has high accuracy, and that it can be used for Structural health monitoring [8]. Through the research literature, it is found that the current research on damage identification of DIC technology focuses on the extraction of damage modes and features. After the strain cloud map is obtained, the stiffness characteristics and other information are still obtained according to the traditional method, and the combination with AI is weak. This paper proposes a quantitative identification method for concrete internal damage based on Deep Learning (DL) and finite element modeling. The performance of the NN is verified based on the measured value of concrete based on DIC, and the non-destructive detection of concrete damage is realized. The innovation is that You Only Look Once (YOLO) technology is introduced into the concrete damage identification model, which improves the detection effect of the model. Most of the previous work still stayed at the level of damage mode and feature extraction, and the damage index was taken as the input of the neural network through preprocessing, instead of directly learning from the data and using convolutional neural network to directly learn the damage features. At present, the research on the internal damage of concrete by using two-dimensional convolutional neural network and digital image correlation method is still in the initial stage. The combination of deep learning and DIC methods in structural damage identification not only obtains the true state of the structure, but also fully utilizes the advantages of neural networks in solving inverse problems, ensuring that a large number of samples can be used as training sets for deep learning, while also ensuring the reliability of neural networks in real structural problems.

The second chapter briefly introduces the characteristics and network structure of YOLO network, the way of prediction output and the composition of Loss function. Based on YOLO, the neural network model required for this study is built, which lays a good foundation for the subsequent network training. Then, the basic theory of DIC and the experimental research content of concrete damage identification based on DIC were summarized, and the prediction effect of neural networks under real concrete damage was verified. The third section provides a detailed analysis of the experimental results, which indicate that DIC technology and deep learning technology can be effectively integrated for the detection of internal damage in concrete, and the overall detection accuracy is high.

In this paper, the article aims to provide a new development direction for the realization of non-destructive testing inside the concrete. The article introduced the AI-related technologies including NNs, target detection technology, YOLO and DL. The article trained the NN using the Anaconda environment and provided the detailed parameters in the experiments. For the image processing, the article adopted the finite element simulation method and simulated the pictures of each concrete beam. The Root Mean Square Error was adopted to measure the error of each parameter.

II. Methods and Model Design

A. AI and NNs

AI is a discipline that studies and develops human intelligent systems, involving extensive research in robotics, Computer Vision (CV), Natural Language Processing (NLP), and expert systems [9]. In achieving this goal, Machine Learning (ML) is required to provide technical support. The core of ML is to use algorithms to guide computers to use data to obtain appropriate mathematical models. ML is widely used in solving AI problems [10]. Therefore, ML is an implementation method of AI, and it is also the most critical implementation method. ML has become the method of choice for AI to develop helpful software for CV, Automatic Speech Recognition (ASR), NLP, robot control, and other applications [11]. Research on NN has appeared for a long time. Initially, it was a biological concept. After that, AI was inspired by NN, and Artificial Neural Networks (ANN) appeared [12]. ANNs are based on the basic principles of biological NNs. Its theoretical basis is the knowledge of network topology. ANN simulates the processing mechanism of complex information by the nervous system of the human brain [13]. Like the human nervous system, the NN is a complex network structure composed of many simple neurons connected and transmitted, as shown in Fig. 1.

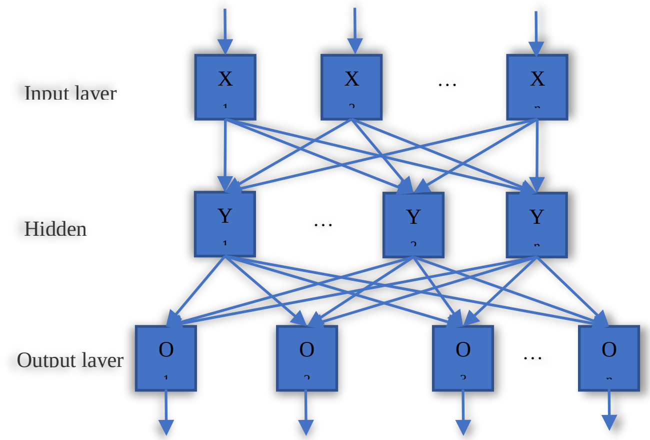

Fig. 1. ANN

DL enables many applications of ML and expands the field of AI. DL has enabled AI systems to achieve significant performance improvements in many important problems such as CV, ASR, and NLP. It has become the key to the current breakthrough of AI [14]. Fig. 2 shows the relationship of AI-related concepts.

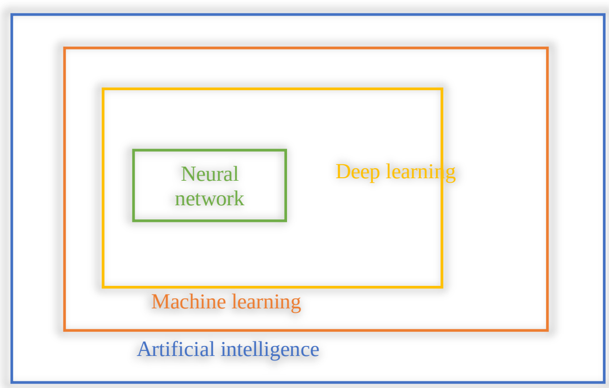

Fig. 2. Relationship of AI-related concepts.

B. Target Detection Technology

Target Detection (TD) uses the powerful computing ability of computers to find objects of interest in an image or video and determine their location and size. TD is a key problem in CV [15]. Since the era of DL, the development of object detection has focused on two directions. The first is the Two-

Stage algorithm, such as the Region-Convolutional Neural Network (R-CNN) series. The second is the One-Stage algorithm, such as Single Shot MultiBox Detector (SSD) [16]. The Two-Stage algorithm needs to generate Proposal and then perform fine-grained object detection. The One-Stage algorithm extracts feature directly in the network to predict object classification and location [17]. In the Two-Stage algorithm, Faster R-CNN structurally integrates feature extraction, candidate region extraction, target box regression, and classification into an end-to-end network. The comprehensive performance, especially the detection speed, has been dramatically improved. So, Faster R-CNN has become the classic network of Two-Stage. In the One-Stage algorithm, SSD converts detection into regression and completes target positioning and classification. A similar Prior Box concept is proposed based on the prior box concept in Faster R-CNN. In addition, the detection method based on the feature pyramid is added. Targets are predicted on feature maps of different receptive fields. Compared with Faster R-CNN, Prior Box has obvious speed advantages and has become the classic One-Stage network [18].

C. Design of Damage Identification Model Based on YOLO and DL

1) Introduction to YOLO: YOLO is an object identification and localization algorithm based on DNNs. This algorithm is a typical one-stage TD algorithm. The core idea is to use the entire image as the network's input and directly return the position of the bounding box and its category at the output layer [19].

YOLO has some unique advantages in the algorithm. These advantages are advantageous for identifying damage within concrete. First, YOLO is very fast at detecting objects. The detection process is simple. The image to be tested is input into the NN to output the detection result. Therefore, the detection speed can be improved a lot. The standard version of YOLO can process 45 images per minute on the Titan X GPU [20]. The traditional Two-stage network has low detection efficiency, but it can be trained with the help of the network pre-trained by the algorithm designer, which can greatly speed up the training process. The image cardinality of this paper is large. There are ten thousand images of concrete beams alone, and the images are all self-made. There are no pre-training parameters for reference, so detection efficiency is essential. Moreover, YOLO's AccessPoint (mAP) is more than twice that of other previous real-time object detection systems, achieving high accuracy in real-time detection algorithms. In addition, YOLO can learn generalization features of objects. Existing tests have shown that YOLO's performance is much better than the object detection systems before DPM and R-CNN when using artworks for testing after it is trained on natural images. It indicates that YOLO can learn highly generalized features, which is helpful for this paper to study the learning of the information projected by internal damage to the concrete surface [21].

2) Network structure: Factors such as input accuracy and training duration are considered comprehensively. Darknet-19 is used as the main network for training and testing. Fig. 3 displays the structure of Darknet19.

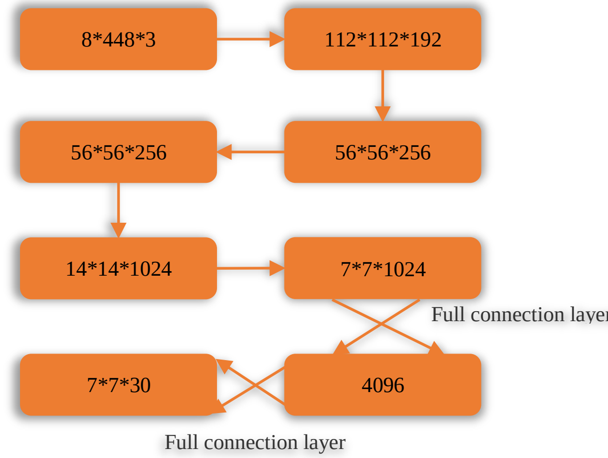

Fig. 3. Schematic diagram of darknet-19 network structure.

The Darknet-19 network is improved based on the GoogLeNet classification network structure. It refers to the experience of the Visual Geometry Group network. It uses a 3×3 convolution kernel and doubles the number of channels after each pooling layer. The Darknet-19 network draws on the idea of the Network in Network and uses global average pooling at the end of the network. The 1×1 convolution kernel is placed between the 3×3 convolution kernels to compress the features, improving the abstraction ability of the convolution layer. Meanwhile, the batch normalization method is used in each network layer. The neurons in the NN of each layer that gradually deviate with the training are pulled back to the standard normal distribution with a mean of zero and a variance of one and normalized. The purpose of stable model training is achieved while improving the training speed.

3) Prediction of the output: YOLO has two different approaches to predicting the output. YOLO-v1 uses a method of directly regressing the position of the bounding box, which can utilize the complete information on the entire image. The a priori frame is referenced when predicting from YOLO-v2, and the bounding box size of the final detection is fixed to 9 types. Different sizes of a priori frames are used for detection on various receptive fields, which can improve the recall rate of the prediction results but reduce the prediction accuracy. Besides, the Intersection of Union (IoU) of the predicted bounding box and the ground-truth box is also affected by the size of the prior box. The types of damage are not distinguished here, and the classification requirements of the NN are not high. In contrast, the regression requirements of the damage location are high, so the direct regression bounding box method is selected to predict the output.

4) Loss function: The loss function is a measure used to evaluate the degree to which the model's predicted value differs from the true value. The better the loss function, the better is the model's performance in general [22]. The loss function of YOLO-v1 consists of four parts: center coordinate error, width and height coordinate error, confidence error, and category prediction. The TD here adds the positioning in the depth direction, as shown in the following equation.

$$Loss = Loss_{xy} + Loss_{wh} + Loss_{oc} + Loss_{noc} + Loss_{c} + Loss_{d} + Loss_{IoU} \quad (1)$$

In Eq. (1), $Loss_{xy}$ refers to the loss function of the center coordinate prediction part. It can be expressed as:

$$Loss_{xy} = \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{obj} \left[\left(x_i - x_i \right)^2 + \left(y_i - y_i \right)^2 \right] \quad (2)$$

In Eq. (2), I_{ij}^{obj} is used to determine whether the jth box in the ith grid is responsible for the prediction of the object. If the grid contains objects, the value is one. If not, it is zero. λ_{coord} is the loss weight coefficient, which is generally five. x_i and y_i are the coordinates in the x-direction and y-direction, respectively, within the bounding box. S^2 is the area of the prediction box, and B is the area of the ground-truth box.

$Loss_{wh}$ refers to the loss function of the width and height coordinate prediction part. It is expressed as:

$$Loss_{wh} = \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{obj} \left[\left(\sqrt{w_i} - \sqrt{w_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{h_i} \right)^2 \right] \quad (3)$$

In Eq. (3), w_i and h_i are the coordinates in the width and height directions of the predicted bounding box, respectively.

$Loss_{oc}$ is the loss function for the confidence prediction of bounding boxes containing objects.

$$Loss_{oc} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{obj} \left(C_i - C_i \right)^2 \quad (4)$$

In Eq. (4), C_i represents the predicted bounding box.

$Loss_{noc}$ is the loss function for the confidence prediction without the object's bounding box.

$$Loss_{noc} = \lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{noobj} \left(C_i - C_i \right)^2 \quad (5)$$

In Eq. (5), λ_{noobj} is the weight coefficient generally 0.5.

$Loss_c$ refers to the loss function of category prediction.

$$Loss_c = \sum_{i=0}^{S^2} I_{ij}^{obj} \sum_{c \in classes} \left(p_i(c) - p_i(c) \right)^2 \quad (6)$$

$Loss_d$ refers to the loss function of depth coordinate prediction.

$$Loss_d = \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{obj} \left[\left(s_i - s_i \right)^2 + \left(d_i - d_i \right)^2 \right] \quad (7)$$

In Eq. (7), d_i represents the value of the pier concrete beam in the depth direction.

$Loss_{IoU}$ refers to the loss function of the prediction of the intersection and ratio.

$$Loss_{IoU} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{obj} \left(IoU - IoU \right)^2 \quad (8)$$

In Eq. (8), IoU measures the accuracy of detecting corresponding objects in a specific dataset.

The loss function adds depth-wise and cross-union ratio predictions. If each part's weight loss in YOLO-v1 continues to be used, the NN cannot achieve good results. Therefore, the above loss function combination is used as the loss in the network construction and debugging stage. After the network debugging is completed, the parameters are adjusted, and the loss function is recombined according to the error of the test results, which can ensure the accuracy of the NN learning.

D. *Training and Testing of Concrete Damage Identification NN*

1) Network training and testing process: According to the damage identification NN designed by YOLO above, the process of training and testing its NN is shown in Fig. 4.

2) Dataset source: Images of concrete damage in civil engineering are collected and modeled in batches using finite element software. The exported images are used to make datasets for DL.

3) Experimental environment: The NN is trained using the Anaconda environment, and Table I reveals the parameter settings in the environment.

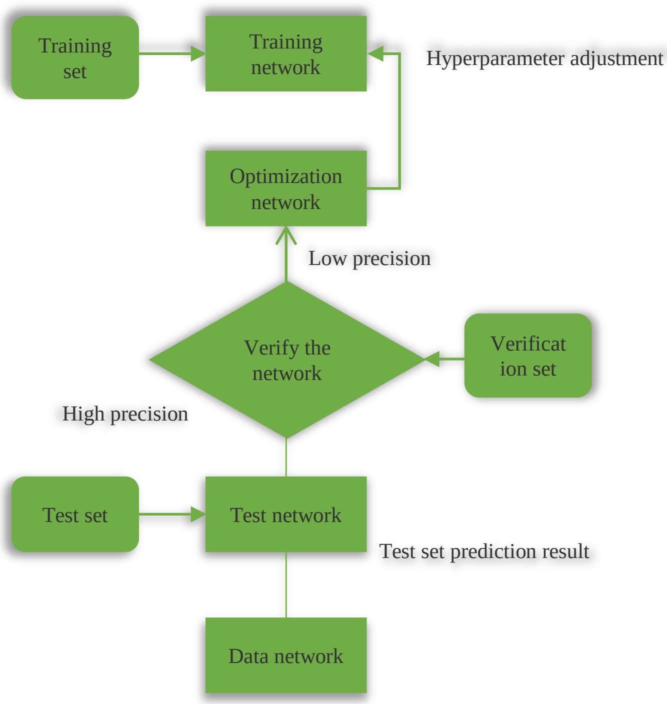

Fig. 4. NN training and testing process.

TABLE I. EXPERIMENTAL ENVIRONMENT AND PARAMETER SETTINGS

Parameter Name	Value
System language	Python3.8
Editor	Py Charm
GPU (Graphic Processing Unit)	Titan RTX (Ray Tracing Texel eXtreme)
Server bits	64
Graphics card name	NVIDIA Titan RTX
Graphics memory	24G
Epoch	25
The number of training sets for a single learning	
Loss function	Equation (1)

E. Concrete Damage Identification Method Based on DIC Technology

1) DIC technology: The basic theory of the DIC method is to obtain the surface displacement deformation by extracting the differential information of the surface of the object. The natural speckle on the object's surface can be directly used, and the speckle can be artificially produced. The gray gradient is the carrier of the deformation information of the structure surface. Artificial speckles can increase the number of feature points on the surface of the object under test, thereby increasing the gray value of the surface under test. The displacement of the feature points in the coordinate system before and after the deformation is calculated by the correlation algorithm to determine the deformation value of the whole image [23].

2) Correlation function: Before calculating the correlation algorithm, it is necessary to discriminate and define the degree of matching between the sample sub-region and the target sub-region, so a correlation function is introduced. The correlation function is the function of the deformation parameter to be obtained. The DIC method calculates the similarity of the two sub-regions before and after deformation using the gray gradient value of the speckle image to get an accurate deformation parameter estimation. Commonly used criteria can be divided into cross-correlation and variance synthesis criteria according to the algorithm [24].

3) Error analysis of displacement measurement: The displacement measurement accuracy of the DIC method is affected by the specimen's gray gradient, the equipment's imaging system, and the related algorithms. The role of speckle is to improve the characteristics of the specimen surface. During the test, a series of problems, such as the difference in the grayscale gradient of the speckle image, the reflection on the component's surface, and the change of the light during the test, will affect the clarity of the image capture. The imaging system inevitably produces errors due to device angle, camera lens position, and quality differences. The clarity of the image will be affected due to a series of problems, such as the difference in the grayscale gradient of the speckle image, the reflection on the component's surface, and the change of light during the test. At the algorithm level, selecting the sub-region size, interpolation algorithm, and shape function of the study area will cause different systematic errors in the calculation [25].

4) Camera calibration: Camera calibration is the process of obtaining the internal and external parameter matrices of the camera. The internal and external parameter coefficients obtained through calibration can be used to correct the images captured by the camera later to obtain images with relatively small distortions. The accuracy of calibration directly affects the final measurement results, so it is the most basic and important part of binocular stereo vision [26].

5) Composition of the measuring system: Here, the measurement and reading of the concrete surface information adopt the DIC method. The measurement system consists of hardware and software. The hardware is mainly image acquisition and reading equipment, and the software includes algorithm selection for image correlation operations. It is important to ensure that the environment cannot change greatly during the image acquisition process to ensure the accuracy of the deformation measurement of the structure surface by the relevant algorithm, including the erection position of the camera and the lighting conditions of the structure surface. Therefore, the fill light is erected during the test, and the camera should not move after the erection is completed. The loading process is recorded by a 3D DIC method based on the principle of binocular stereo vision to identify the changes in the concrete surface, reduce the distortion, and prevent the partial out-of-plane displacement of the concrete from affecting the test results. Fig. 5 shows the measurement system of the 3D DIC method [27].

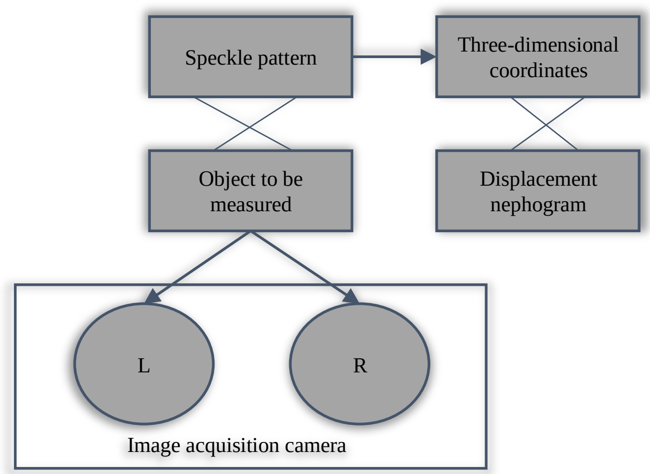

Fig. 5. 3D DIC method measurement system.

F. Concrete Damage Identification Process Based on DIC Technology

According to the relevant theory of DIC technology, the concrete damage identification process based on DIC technology is shown in Fig. 6.

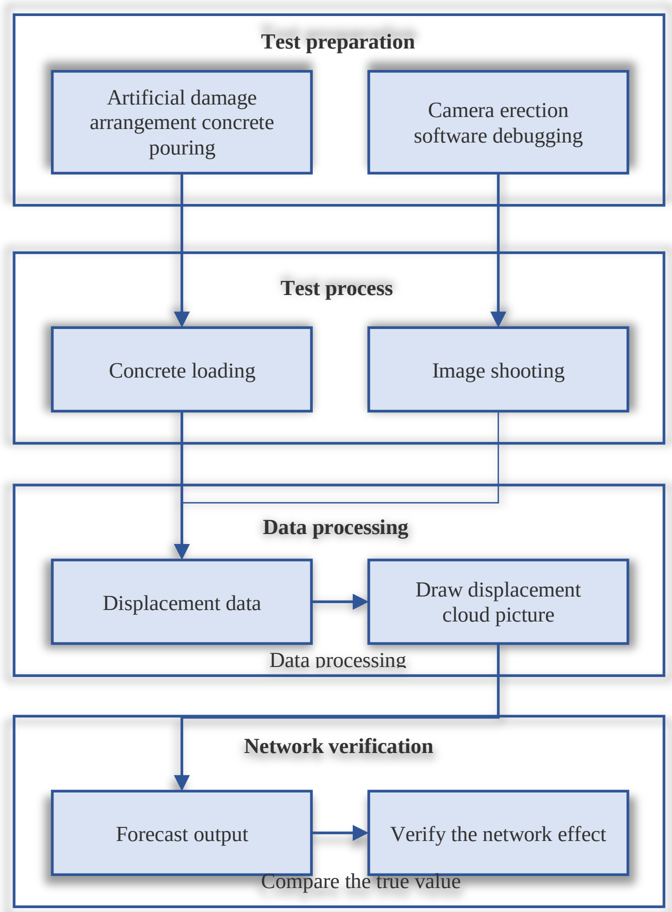

Fig. 6. Concrete damage identification test process based on DIC technology.

G. *Experimental Design*

A total of seven reinforced concrete beams for constructing the wharf are selected in the experiment, represented by A-G, respectively. The dimensions of the concrete beams and the internal reinforcement arrangement are consistent with the finite element modeling results. First, the pictures of reinforced concrete beams are extracted by DIC equipment. Then, the finite element simulation method is adopted, a load of concrete is set to 21kN, and the pictures of each concrete beam are simulated. Finally, the processed images are input into the previously trained NN. The prediction results of seven parameters, including the damage center coordinates, the bounding box's size, and the confidence level corresponding to each image, are generated. The predicted value is compared with the actual size and position of the foam block prevented during the test, and the error of each parameter is obtained. The standard of measurement is the Root Mean Square Error [28].

III. RESULTS

A. *Effect of Damage Model of Wharf Concrete Structure based on YOLO and DL*

1) Concrete beam test results: The NN completes learning after 100 cycles of training with the selected NN. The training situation of the obtained NN is presented in Fig. 7. From Fig. 7, the overall loss of the NN decreases smoothly during the training process. The method of adjusting the learning rate by gradient makes the network converge rapidly in the early stage of training. In the middle and later stages of training, there is no situation where the predicted value exceeds the real value, resulting in a significant rebound in the loss value. During the later stages of training, the validation loss stabilizes at around 0.24. However, the training set's loss value still decreases, indicating that the NN is overfitting, but the overall effect on the validation set is not large.

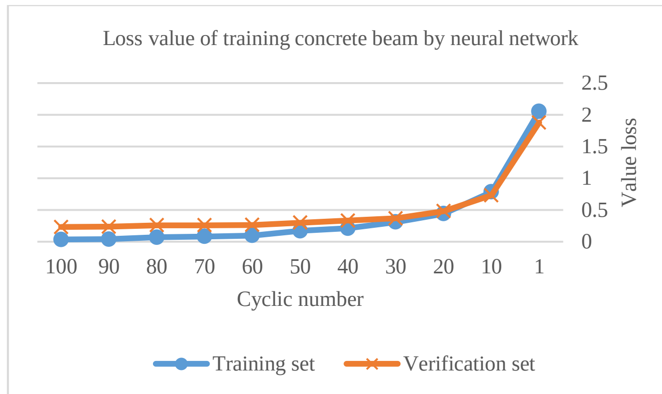

Fig. 7. Loss values for training a concrete beam with an NN.

2) Test results of the concrete column of the wharf: The concrete piles are also trained using the previously selected network for 100 cycles. The judging criteria also use the network loss value and the test set accuracy. Fig. 8 reveals the concrete column test results. Fig. 8 indicates that the overall convergence of the network is good, and the curve is smooth. Compared with the training of concrete beams, the fluctuation of the validation set of concrete piles is more prominent, and there is also some overfitting phenomenon. The loss value stabilizes around 0.38, and the network accuracy is slightly inferior to the concrete beam network. The number of images in the training set of concrete piles is only about 0.14 of that of concrete beams. Therefore, the difference between the loss values of the two is within an acceptable range.

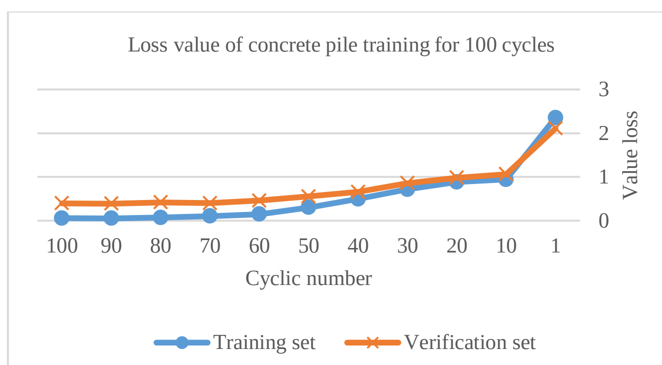

Fig. 8. Loss values for 100 epochs of concrete pile training.

B. *Verification of Concrete Damage Identification Method Based on DIC Technology*

The load on the concrete is set to 21kN. At this time, the processed images are input into the previously trained NN. The prediction results of seven parameters, including the damage center coordinates, the bounding box's size, and the confidence level corresponding to each image, are generated. The predicted value is compared with the actual size and position of the foam block prevented during the test. Fig. 9 shows the error of each parameter. Fig. 9 shows that the errors differ for different concrete beams. The prediction error tends to be large when the concrete damage is minor. The overall data show that the error of each concrete beam is within the acceptable range, and the estimation of the damage position and size of the concrete has been accurate. It shows that the damage identification network constructed here has good robustness.

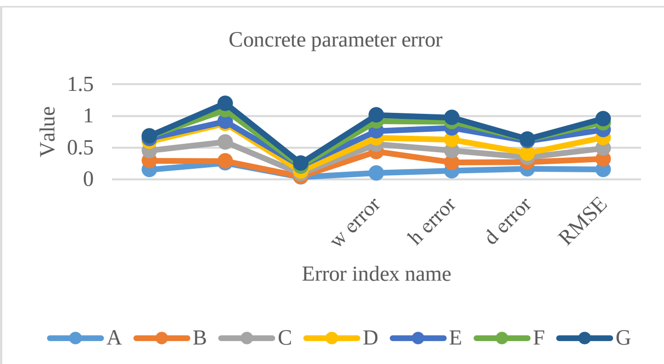

Fig. 9. Concrete beam parameter error.

IV. Conclusion

This paper is the first time to carry out a series of research on the internal damage location of concrete structures based on the plane distribution information in China, and provides a good idea and reference for the follow-up Structural health monitoring and other topics, which has important engineering application value.

To sum up, this paper uses the finite element model to simulate the internally damaged concrete structure. This research article took the position and size of the concrete damage learned and predicted in the DLNN as input. Meanwhile, the article applied the DIC and applied concrete surface parameters in laboratory tests. Then, the NN is input to train again to obtain the identification errors of different concrete structural damages. The results show that: (1) The YOLO algorithm in the one-stage algorithm has the advantages of fast detection speed, strong generalization ability, and low background identification error rate. (2) When predicting the damage size and depth of concrete beams, it is found that the prediction accuracy increases as the damage size and depth decrease. (3) The trained NN has a good prediction effect on each parameter of the concrete structure. The disadvantage is that the NN in this paper is built based on the YOLO algorithm, which can achieve multi-damage prediction. However, due to time constraints, multi-damage structures are not considered in the modeling phase. In subsequent work, multiple damages can be arranged in the concrete members. In the prediction, the non-maximum suppression method can be used to output multiple damage locations at one time. Then, the prediction ability of the NN for multiple damages in concrete is tested. This paper is of great significance and value for applying and promoting prefabricated structures. It also provides new ideas for the damage of concrete internal defects and the batch detection of prefabricated structures. (4) The neural network in this study is built based on the YOLO algorithm and can achieve multi damage prediction. However, due to time constraints, the construction of multi damage was not considered in the modeling phase. In subsequent work, multiple damages can be considered in concrete components, and non-maximum suppression methods can be used to output multiple damage locations at once during prediction, to test the predictive ability of the neural network for multiple internal damages in concrete. (5) In the DIC based experimental verification section, the quality of the concrete surface displacement cloud images generated by some components is poor, which is closely related to hardware equipment, experimental environment, etc. In the subsequent work, a higher lens quality camera can be used for shooting in a more stable environment to ensure the quality of the generated displacement cloud map.

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