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# Deep Learning Model of Reinforced Concrete for Detecting Internal Structural Damage and Comprehensive Evaluation

Haoran Yuan [*]

College of Civil Engineering and Architecture, Wenzhou University, Wenzhou, China

* Corresponding Author Email: 22211410138@stu.wzu.edu.cn

**Abstract.** In recent years, China has achieved world leading achievements in the field of civil engineering, but the aging and damage problems of large structures have become increasingly prominent. Traditional structural health monitoring (SHM) methods have certain limitations and urgently require innovative technological solutions. This article explores existing structural health detection methods, including manual visual inspection, sensor detection, and digital image processing, analyzes their advantages and disadvantages, and provides a detailed introduction to the application of deep learning, especially convolutional neural network (CNN), in structural damage detection. Finally, this article constructs a SHM model based on deep learning, and improves the detection accuracy of the model through dataset construction and enhancement techniques. The research results indicate that deep learning, especially CNNs, exhibits high accuracy and adaptability in SHM, which can effectively compensate for the shortcomings of traditional detection methods. The research on deep learning provides new technological ideas for the construction of future intelligent SHM systems, which is expected to improve the efficiency and accuracy of structural damage detection in the field of civil engineering. In the future, with the introduction of more datasets, deep learning models will be further optimized.

**Keywords:** Deep learning; Convolutional neural networks; Structural health monitoring; Sensor detection; Digital image processing.

## 1. Introduction

Since the 21st century, with the development of the country and economy, China has gradually taken the lead in the field of civil engineering and reached the world's advanced level. At the beginning of the century, China completed a series of large-scale structural projects, such as the Hangzhou Bay Cross Sea Bridge, the Hong Kong Zhuhai Macao Bridge, and the Bird's Nest Sports Center. In these large structures, as the usage time and frequency increase, due to various factors such as design defects, overloading during service, structural aging, the structures will inevitably be damaged, affecting their service life. Therefore, establishing a sound structural health monitoring (SHM) system to timely identify, evaluate, and maintain structural damage is very meaningful. In recent years, with the rise of artificial intelligence technology, various industries have undergone profound changes, and civil engineering is no exception. The flourishing development of artificial intelligence technology coincides with the era background of "large-scale, intelligent, and complex" development in civil engineering. This article will explore the practice and application of deep learning in artificial intelligence for structural detection, compare it with existing damage detection methods, introduce their principles, advantages and disadvantages, conduct systematic analysis and discussion, and summarize and compare them.

## 2. Existing SHM Technology

### 2.1. Manual Visual Inspection Method

In this testing method, testing technicians need to conduct regular visual observation combined with professional instruments for testing, evaluation, and recording. The regular inspection items mainly include the detection of honeycomb surface, peeling angle, holes, concrete strength, concrete carbonation, crack width, protective layer thickness, and steel corrosion. Although this detection method has been effectively tested over time, the subjective evaluation based on the tester's existing experience lacks a scientific and systematic approach, and is also limited by the testing items and results, which can easily lead to misjudgment and misjudgment of structural damage, ultimately causing more serious structural damage and unnecessary economic losses.

### 2.2. Sensor Detection Method

In order to overcome the shortcomings of the above methods, sensor based structural health detection systems are widely used in engineering projects. This system can continuously monitor the health status of the structure, achieve intelligent diagnosis of the location and degree of damage, and effectively evaluate the service condition, durability, reliability, and bearing capacity of the structure.

In sensor detection, common detection items include: (1) impulse echo (IE), (2) ground penetrating radar (GPR), (3) infrared thermal imaging (IRT), (4) resistivity, (5) half cell potential, (6) microwave moisture technology, (7) eddy current, (8) ultrasonic pulse echo, (9) constant current pulse measurement, (10) pulse response, (11) ultrasonic surface wave, (12) chain drag and hammer sound detection, and (13) chloride concentration measurement [1].

However, the implementation of structural health detection systems based on sensor networks faces several challenges. Firstly, due to the large number of items that need to be tested, the testing cost is high and the required time is relatively long. In China, there are only a few higher education institutions with this testing capability. In addition, in the actual testing process, due to various factors, regular testing can usually only be carried out, making it difficult to achieve continuous testing, thereby affecting the continuity and reliability of data [2]. Moreover, the integrated and installed structural health detection system requires professional personnel to operate, which further limits the effective application of distributed detection equipment in large buildings. In summary, sensor based damage detection methods are not a convenient, fast, and cost-effective solution.

### 2.3. Digital Image Processing Method

Digital image processing, also known as computer image processing technology, aims to extract features from images through algorithms and achieve image processing functions such as classification, localization, and segmentation. In civil engineering construction, the main application of digital image processing technology is the detection of structural surface damage, including edge detection, transformation techniques, and feature statistical techniques [2]. However, for damage detection of specific structural types, digital image processing techniques require image preprocessing. In addition, these images exhibit high sensitivity when facing issues such as noise, stains, image distortion, uneven lighting, and shadows, and there is currently no optimal solution [2, 3].

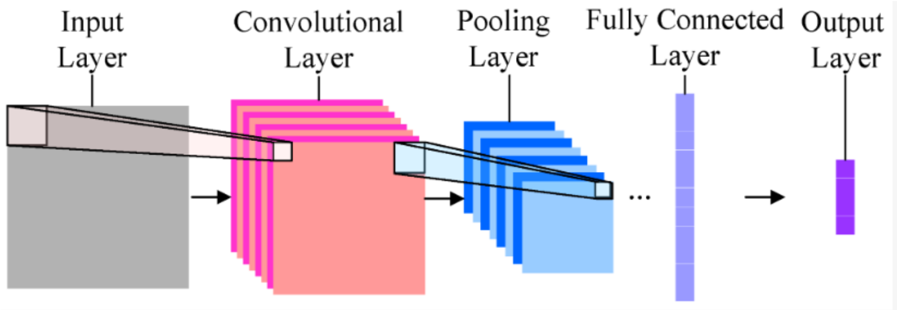
## 3. Deep Learning Algorithms

### 3.1. Deep Learning

Deep learning is a data learning based approach that emphasizes feature extraction through multiple consecutive levels. The basic implementation principle is the same as that of artificial neural networks, which is to mine the features of input data by constructing specific neural network models. This implementation form is called deep neural networks [4]. Common deep learning models include (1) Recurrent Neural Network (RNN), (2) Generative Adversarial Network (GAN), (3) Convolutional Neural Network (CNN), (4) Deep Belief Network (DBN), and (5) Deep Reinforcement Learning (DRL) [5]. Among these models, CNN is the earliest and most widely used type to achieve success.

### 3.2. CNN

The characteristic of CNN is that they draw inspiration from the visual cortex of animals and can process large amounts of image data to accurately identify the category to which an object belongs, and then measure its credibility using classification probability. As shown in Fig. 1, a convolutional neural network generally consists of the following five layers: input layer, convolutional layer, pooling layer, fully connected layer, and output layer. The advantage of CNN is that they use convolutional computation to gradually extract abstract features and utilize these features to complete tasks [6]. However, traditional CNN often require a significant amount of time to construct datasets, so Tangokan et al. from the University of Manitoba proposed a novel pixel level concrete crack detection method that improves recognition speed and accuracy [7].



**Figue 1.** General CNNs [8]

#### 3.2.1. Convolutional layer.

The most important thing in CNNs is the convolutional layers. The task of a convolutional layer is to detect the features of the previous layer and take the output of the previous layer as the input of that layer. The convolutional layer performs a multiplication and addition operation on a specified number of weight matrices called convolution kernels, and finally obtains the convolutional output of that layer. This calculation method greatly reduces the number of parameters, accelerates the learning rate, and to some extent reduces the impact of overfitting.

#### 3.2.2. Pooling layer.

The pooling layer is the next layer of the convolutional layer, also known as the name sampling layer. Its effectiveness lies in reducing the width and height of neurons while maintaining the same depth in data processing operations, effectively reducing the input size of data, reducing overfitting during training, and ensuring that key information of input data is not lost. The two common forms of pooling layers are mean pooling and max pooling, with max pooling being the most commonly used. Studies have shown that in image datasets, the effect of maximum pooling is greater than that of mean pooling [6]. Maximum value pooling not only significantly reduces the computational load of data, but also downsamples the feature map, making the model less sensitive to changes in the numerical positions in the input feature map, thereby improving the stability of the network model.

#### 3.2.3. Fully connected layer.

The fully connected layer is located after the convolutional layer and pooling layer in CNNs, often serving as a classifier [2]. As shown in Fig. 2, after convolution calculation, the input layer enters the fully connected layer for processing and outputs independent data. The effect is to remove spatial information from the data, transform the three-dimensional matrix into a one-dimensional vector, and map the feature data learned by the convolutional and pooling layers to the sample space. In practical operation, fully connected layers can be convolved to associate and combine all relevant weight parameters, providing guidance for the learning process.

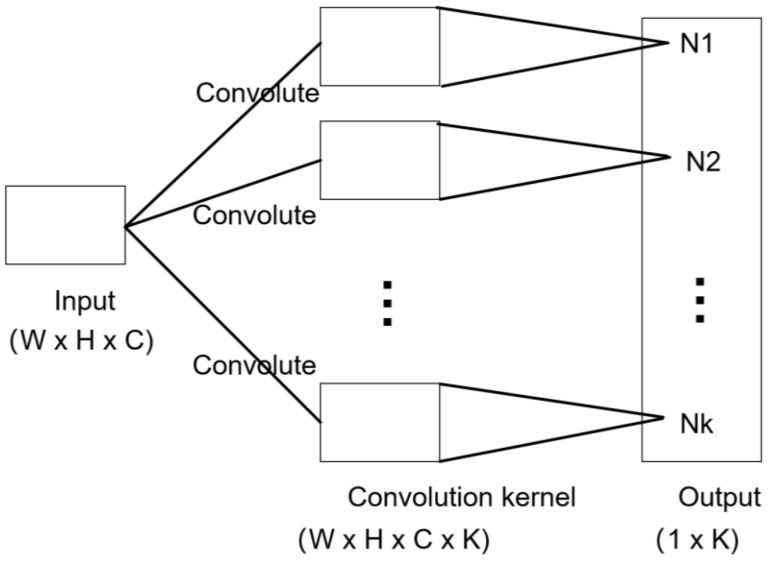


**Figure 2.** Fully connected layer

### 3.2.4. Activation layer.

The activation layer, also known as the random activation layer or activation layer, aims to solve nonlinear problems in network training. Common activation functions include ReLU function, Sigmoid function, and tanh function. The ReLU function is the most common in the field of deep learning. Compared to the other two functions, the ReLU function only requires one threshold for computation, greatly reducing the computational load, improving the efficiency of machine learning, and saving computing resources. And the ReLU function also has the advantage of not being easily saturated, solving the problem of computing power saturation that often occurs with Sigmoid and tanh functions [2].

### 3.2.5. Softmax layer.

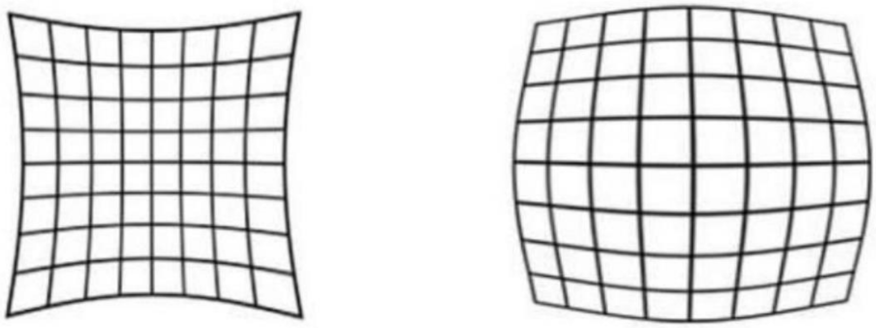
In CNNs, selecting the appropriate output layer is crucial for the accuracy of classification results. This layer is usually located at the end of the entire neural network architecture. The Softmax layer is the most commonly used classifier in neural networks. It uses the Softmax formula to convert input data into the probability values of each sample's category, thereby achieving accurate category prediction. In the softmax layer, it is necessary to estimate each classification result, determine the type of input data according to the size of each probability value, and then normalize it to make the sum of all probabilities equal to 1.

## 3.3. Establishing Dataset

### 3.3.1. Dataset collection.

In the study of different structural damages, the required target images also vary. In general, it is possible to utilize publicly available and widely accepted databases on the internet, such as ImageNet, PASCAL VOC, and MS COCO, or manually obtain a sufficient number of images using cameras [9]. Artificially obtained images need to consider covering various types of images, including but not limited to various lighting, occluded shadows, stains, pseudo cracks, marker numbers, etc., to ensure that the training model can adapt to various complex environmental conditions. When manually collecting data, in order to expand the sample size of the dataset, the idea of "image augmentation" can be adopted. When shooting, rotate the shooting equipment and take "multi angle" and "multi azimuth" shots from "front", "left front", and "right front" respectively. This method can effectively increase the sample size [10].

When using a camera for manual acquisition, optical distortion of the camera is also a factor that needs to be considered. Optical distortion is divided into radial distortion and tangential distortion. Radial distortion comes from the shape of the lens, including pillow distortion and barrel distortion, as shown in Fig. 3. Tangential distortion comes from the entire assembly process of the camera [11]. The barrel distortion mainly occurs at the edges and corners of the image, which has a significant impact on target tracking and displacement calculation. By using the method of displacement of isolation bearings, the influence of distortion on displacement calculation can be ignored in the central area of the image.



(a) Pincushion (b) Barrel distortion

**Figure 3.** Radial distortion [11]

### 3.3.2. Dataset calibration.

The calibration of the dataset includes labeling and judging the images, removing redundant information, and expanding the dataset. The main significance of marking judgment is to pre identify cracks. In this dataset, images with cracks are identified as positive samples, while images without cracks are considered negative samples [12]. Marking cracks is a labor-intensive, repetitive, and tedious task, but this process is crucial for improving the recognition accuracy and efficiency of neural networks. Finally, Liu Shengxin's team from Harbin Institute of Technology constructed a crack marking database that corresponded one-to-one with the original image database [10]. The reason for removing redundant information is that, due to the need to use markers to represent cracks, black markers are easily mistaken for cracks, which can cause errors in image digitization processing. Therefore, manual elimination of marker numbers is required [1]. At the same time, due to limitations such as site and environmental conditions, some images have poor imaging effects and may have problems with blurring and noise. Therefore, traditional image enhancement and noise removal operations need to be performed on this part of the image. This can further simplify the image training data, improve the efficiency and algorithm effectiveness of the network model. Trimming images is also crucial in removing redundant information. Due to the large size of the raw images captured by the camera, it is easy to consume a lot of memory during the training process of neural networks and significantly reduce computational efficiency. In the case of a large number of samples, the time required to complete one training session will significantly increase, so it is necessary to control the size of the input image to ensure normal training [7].

### 3.3.3. Dataset amplification.

When keeping the neural network model and its parameters unchanged, the greater the diversity of samples and the number of effective samples, the more stable and accurate the training results will be, and the robustness will also be significantly improved. Compared to traditional machine learning methods, deep learning requires a larger number of samples. The team led by Liu Shengxin from Harbin Institute of Technology used data augmentation to increase the number of original training images, resulting in a more generalized model [10]. The common methods for amplifying datasets include random cropping of images, random color jitter, random Gaussian noise, and random rotation. After processing, images of cracks located at the corners should be ignored. Because neural network models cannot accurately identify whether these crack features are indeed cracks, and may lead to errors in the annotation of the training dataset. In addition, even if trained networks can classify these images, it becomes impractical to verify whether the predicted results are false positives or true positives due to the difficulty of identifying crack features [7].

## 4. Conclusion

This paper mainly studies the application of deep learning in artificial intelligence for structural health detection. Combining existing detection techniques, it deeply analyzes the advantages and disadvantages of various methods and proposes an innovative solution based on CNNs. Based on the research results, this article draws the following conclusions:

(1) The manual visual inspection method relies on the experience of the testing personnel, which is highly subjective and prone to misjudgment, resulting in high maintenance costs in the later stage. Although the sensor detection method has high accuracy, its equipment and implementation costs are high, and it is limited by the continuity of data and on-site conditions, making it difficult to achieve real-time detection. The digital image processing method has to some extent alleviated the subjectivity of manual visual inspection, but its stability in complex environments is poor, and it is easily affected by external factors such as noise and uneven lighting, resulting in insufficient recognition accuracy. In summary, traditional detection methods have their own shortcomings and are unable to meet the needs of modern civil engineering for large-scale SHM.

(2) CNN can automatically extract features from large amounts of data by combining multiple layers of convolution, pooling, and fully connected layers, and have strong nonlinear modeling capabilities. This enables it to detect structural damage more efficiently in different complex environments, especially in image data processing, where CNN has shown significant advantages. By constructing and training a deep learning model based on a crack dataset, experiments have shown that CNN can effectively improve the accuracy of crack detection and overcome the limitations of traditional methods in complex backgrounds. In addition, the expansion and calibration of the dataset also play a key role in improving the model's generalization ability.

(3) Although this study demonstrates the enormous potential of deep learning in SHM, there are still some shortcomings in this field. Firstly, deep learning has high requirements for the size and quality of datasets, but currently related datasets are relatively scarce, especially in different usage scenarios where data acquisition is difficult and costly. Secondly, although deep learning models perform well during the training process, their real-time performance and resource requirements remain challenges in practical applications. In addition, the black box nature of the model makes its interpretability poor, which poses a challenge to the credibility of engineering applications. Future research should further expand the size of the dataset, especially by collecting data from multiple perspectives and scenarios, in order to enhance the model's generalization ability. Meanwhile, in response to real-time issues, detection efficiency can be improved through optimization algorithms and hardware acceleration. In addition, the interpretability of deep learning models is also a key research direction in the future. Only with higher transparency and interpretability can deep learning be widely applied in the field of civil engineering.

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