Image processing of Casting defects based on Convolutional neural network

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Abstract. At present, there are numerous losses caused by corrosion cracking of metal castings in engineering in China. In order to detect the possible defects of metal castings in engineering, the laser ultrasonic vision inspection technology is used to image the castings, and then the identification efficiency is low. In order to process these images efficiently and quickly, convolutional neural network image processing technology is introduced. According to the actual needs, a convolutional neural network architecture is designed to recognize images, and whether the architecture meets the requirements is verified. Experimental results show that the performance of the architecture meets the design requirements. Under the same conditions, this structure provides a solution for casting defect detection combined with artificial intelligence.

1. Introduction

In the process of using metal castings in engineering, the castings are often damaged by high strength load. Harsh environment will also cause irreparable damage to the surface of the castings, and may even make the castings unusable. These damages are common problems in industrial environment, such as cracks in castings during use. The existence of cracks not only causes the failure of castings, but also causes safety problems and endangers social security and economy. So it is necessary to find these problems.

In recent years, nondestructive testing (NDT) technology has brought great safety and economic benefits to society because of its advantages. NDT is a comprehensive technology that uses various physical phenomena to detect defects on the premise of ensuring the integrity of the tested goods. As one of the nondestructive testing techniques, laser ultrasonic NDT has been widely used because of its wide application range, good description of defect characteristics and high detection efficiency.

Laser ultrasonic nondestructive testing technology is to use pulse laser to generate ultrasonic stress pulse inside the object under test without damaging the object, and thus stimulate a variety of different signals, these signals will spread various information of the component under test. Finally, reflection, scattering and attenuation of the signal are collected to describe the defect characteristics. Laser ultrasonic visualization detector is mainly divided into three parts: laser emission controller, ultrasonic probe and laser ultrasonic testing equipment control. The laser emission controller generates excitation to the measured casting and receives the signal through the ultrasonic probe. The laser ultrasonic testing equipment collects and visualizes the signal waveform. The visualization is to output the signal as an image. Based on the laser ultrasonic detection technology, the neural network is used to identify the
defects in the collected images quickly and efficiently.

2. Image preprocessing
The experiment in this paper only needs to judge whether the image is defective, and does not need to make more judgments. In order to improve the detection efficiency, the image is preprocessed before image recognition. The preprocessing is to convert the three-channel image to the single-channel image, and then unify the resolution of the gray image. The processed image is shown in Figure 1.

![Grayscale sample image](image)

According to the analysis of Figure 1, it can be found that due to the large noise interference of the image, it is difficult for general image processing methods to determine whether the maximum amplitude map is defective. Therefore, this paper proposes to use a convolutional neural network [1] (CNN) to identify the image.

3. Convolutional neural network
CNN made a series of calculations using convolution to check each pixel point of the image and used the result as the pixel value of the output image. CNN neurons can quickly and efficiently complete image processing by responding to surrounding units. The recognition effect can be controlled by changing the structure of CNN, and the changes of CNN’s unique convolutional layer, convolutional kernel and pooling layer can bring different recognition effects to CNN, so as to find the best recognition effect. Compared with general image processing technology [2], CNN’s unique image processing method not only provides new ideas for image processing technology, but also brings rapid development of image processing technology.

3.1. Convolutional layer
Convolution is a method to extract input image features in CNN. It is a forward propagation method using square convolution kernel to traverse the input image, weighted summation and bias of overlapping parts. The calculated pixel value is taken as the pixel value of the output image, and so on, an output can be completed by traversing an image. As shown in Formula (1) and Figure 2.

\[
o = \frac{n + 2p - f + 1}{s}
\]

Where \( n \) is the length and width of the output image, \( p \) is the length and width of the input image, \( p \) is the padding size, \( f \) is the filter size, and \( s \) is the stride size.
Figure 2. Convolution layer computation

As CNN is a practical study far beyond theory, most of the current CNN convolution layer settings are based on experience or experimental verification. In this paper, two-layer convolution and three-layer convolution are compared to find the best convolution layer structure.

3.2. Filter
Filter is the key to extract input image features. The structure of the filter is W*D*C, corresponding to length, width and height respectively. Usually the length and width are equal. C is the number of image channels. In order to improve the recognition efficiency, the sample image is preprocessed with gray scale, so the number of channels in the input image is 1. Because the size of the filter only improves the accepted field if it is greater than 1, the filter generally does not accept 1. Because uniform filtering will cause feature shift and affect the recognition effect, singular filtering is usually used. In general, the length and width of the filter are 3 x 3.

3.3. Pooling
Pooling layer[3] is a method of down-sampling, and the calculation method of pooling layer is the same as equation (2). Common methods are maximum pool, minimum pool, and average pool. Because maximum pooling can retain the maximum value of input image information and retain more details in feature extraction, this paper chooses maximum pooling method, as shown in Figure 3. The purpose of pooling layer is to reduce parameters. In this paper, a pooling layer is added after the two convolution layers (2 and 3) to reduce calculation parameters.

3.4. Activation function
The function of activation function[4] is to add a nonlinear factor into the calculation of CNN. If the activation function is not applied in CNN, the calculation of each layer is related, so that the output of the last layer is linear with the input of the first layer. Since defect detection only uses a computer to judge whether there are defects in the image, Sigmoid function is commonly used for binary classification processing, and this function is also used as the activation function in this paper. Formulas
(2) and (3) are Sigmoid functions and their derivatives.

\[ f(x) = \frac{1}{1 + e^{-x}} \]  

(2) 

\[ f'(x) = f(x) \cdot (1 - f(x)) \]  

(3) 

3.5. Fully connected layers

The full connection layer (FC) plays the role of classifier in the whole convolutional neural network. If the operations of the convolution layer, pooling layer and activation function layer are to map the original data to the hidden layer feature space, the full connection layer is to map the learned "distributed feature representation" to the sample marker space. It is called fully connected because each neuron is connected to each neuron in the adjacent layer. As shown in Figure 4, a simple two-layer fully connected network is characterized by input and predicted by output.

![Fully Connected Layer](image)

Fully Connected Layer

Figure 4. Fully connected layer

3.6. Architecture of convolutional neural network

To sum up, THE CNN structure based on this experiment is designed. Figure 5 shows the two-layer structure of three convolution layers and one pooling layer. After preprocessing, the image to be detected is entered into CNN. First, feature images are processed by convolution layer, and then feature images are down-sampled by pooling layer. Finally, the pixel value of each pixel point in the image is extracted in the full connection layer and output as a one-dimensional array. After full connection layer processing, classification, recognition and output are carried out according to the pre-designed convergence degree. Finally, the computer can determine whether there are defects in the image.
4. Experiment and analysis

In this experiment, the sample data was divided into two large groups, and each large group was divided into four large groups. Large groups are distinguished by the number of convolution layers. Each group uses a different number of samples as a distinction, and the number of samples shows an increasing relationship. Figure 6 shows the recognition rate of 8 groups of data.

| conv | Recognition rate | Average rate |
|------|------------------|--------------|
| 2    | 71%              | 77.25%       |
| 3    | 90%              | 89%          |

According to the analysis in the above table, the recognition rate of the three-layer convolutional layer is generally higher than that of the two-layer convolutional layer in the case of the same samples. The experiment proves that the recognition accuracy of CNN will increase with the increase of the number of convolutional layers, because the more convolutional layers, the more parameters, which is conducive to image recognition. Finally, the experiment proves that CNN is not fast enough in casting image defect processing, but the recognition effect is good.
5. Conclusion
In this paper, CNN image processing technology is applied to image defect processing of castings, and the reliability of CNN structure is tested on this basis. Experiments verify a feasible and efficient CNN structure, which combines artificial intelligence technology with traditional engineering field, and provides a method for image processing of casting defects. In this paper, the application of CNN is relatively simple and the recognition rate is relatively general, but the recognition rate meets the requirements. In the following work, we will focus on finding a faster and more effective image defect recognition structure.

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