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Development of an automatic detector of cracks in concrete using machine learning

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Abstract

This study is to develop a detector that automatically detects cracks from the photographs of concrete structures, using convolution neural network which is a kind of deep learning. Firstly, photographs of concrete were collected for the learning data. Secondly, pictures of cracked part, chalk letter part, joint part, surface part and others part were produced from these photographs for the dataset. Thirdly, classifier to classify into these 5 class from pictures was created using the dataset and convolution neural network. Finally, the automatic detector was produced using this classifier.

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Keywords: machine learning; deep learning; cracked concrete; automatic detection

1. Introduction

Recently, the aging of structures is becoming a serious problem, and the amount of maintenance works increases accordingly to keep structure healthy and operational. In order to reduce the maintenance work cost, it is useful to develop a detector which automatically detects cracks in concrete from the photographs of structures. On the other hand, deep learning has attracted attention in the field of image recognition recently [1,2]. Deep learning is a machine learning method using an artificial neural network which mimics the neural networks of a brain. In the benchmark tests of image recognition, the image recognition technology using deep learning sets a new record over the past one, showing its usefulness in the field [3]. Based on these, by using deep learning in the image recognition,

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it is considered possible to expect a sufficient detection accuracy of cracks in concrete. This study is to develop a detector that automatically detects cracks from the photographs of concrete structures, using convolution neural network which is a kind of deep learning.

2. Convolution neural network

A convolution neural network is a machine learning method specific to image recognition. By convolution, it is possible to extract feature in an area rather than at a point and universality against deformation and movement of the image can be acquired.

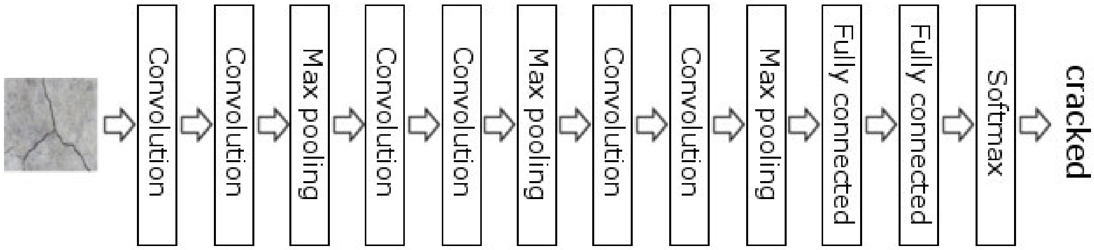


Fig. 1. Convolution neural network.

2.1. Convolution layer

Convolution layer is a layer performing the convolution of the feature. Pattern in images is to be detected by the convolution of the feature. The feature is automatically acquired by learning. Output image convolution of filter is called feature map.

2.2. Pooling layer

Pooling layer discards some information as to the strong response of the filter at any position of the image, and implements the universality of responses to the features appearing in the image. Placing and raster scanning $H \times H$ pixel region on the $W \times W$ pixel input image, the maximum value is taken from the area by max pooling. For example, there is 4×4pixel image as Fig. 2.(a). As the maximum value is taken from each 2×2 pixel area by max pooling, this image is changed to Fig. 2.(b).

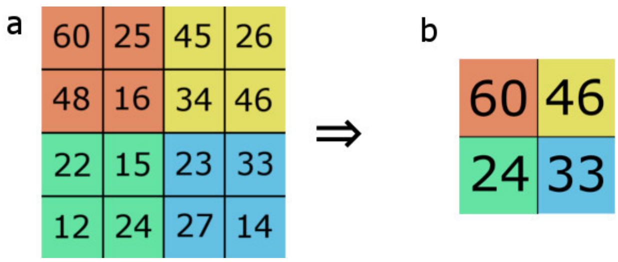


Fig. 2. Pooling layer.

2.3. Fully connected layer

Extracted feature from convolution layer is input to fully connected layer and fully connected layer learns the feature for classification.

2.4. Softmax

Softmax is used to output layer of the multi-class classification of the network. It indicates a probability that the input image is classified into each class. The input image is classified into class of maximum probability.

3. Learning dataset

Firstly, photographs of cracked concrete such as Fig. 3 were collected about 2000 sheets. Secondly, pictures of cracked part, chalk letter part, joint part, surface part and others part such as Fig. 4 were produced: 5335, 2761, 4223, 1533 and 4020 pieces of images respectively from these photographs. Thirdly, by horizontal inversion and cutting out the four corners, the number of images were expanded up to 10 times more. Finally, by resized the images to 64×64pixel, the learning dataset was prepared.

Fig. 3. Photo of cracked concrete

Fig. 4. Learning dataset

4. Method of learning and evaluation results

After subtracting the RGB average of the pixels in each image of the collected learning dataset, the neural network parameters in Table 1 were used in the learning for 30 times as 5class classification. The activation function of convolution layer and fully connected layer uses ReLU. Output calculation, gradient calculation can be faster by ReLU. LReLU is ReLU given a little slope to the negative side. Also, dropout is used in convolution layer and fully connected layer. As dropout is to disable the node every time of learning, it prevents overtraining of the network. Also, each node does not expect the activities of the other nodes and learns to identify independently.

To experiment, GPU instance of Amazon Web Service was used. In machine learning, to calculate by the GPU is faster than to calculate by the CPU. AWS is cloud computing supplied by Amazon.com, Inc. It is possible to build a temporary high-performance environment at a low cost by AWS.

Conducting 2 class classification of cracked concrete and others and, 3 classification of cracked concrete, chalk letter and others, evaluation was conducted by using each 1000 new pictures of cracked concrete, chalk letter and others. The results are shown in Fig. 5. Max value of 2 class classification is 79.9% and 3 class classification was 73.3%. Incidentally, calculation time was about 4 hours.

Table 1. Network parameter

Layer	Kernel	Stride	Feature map	Function	Dropout
data	-	-	64×64×3	-	-
conv1	11×11	1	64×64×16	LReLU	0.2
conv2	5×5	1	32×32×32	LReLU	0.3
pool2	3×3	2	32×32×32	-	-
conv3	5×5	1	32×32×32	LReLU	0.3
conv4	3×3	1	32×32×32	LReLU	0.3
pool4	3×3	2	16×16×32	-	-
conv5	3×3	1	16×16×32	LReLU	0.3
conv6	3×3	1	16×16×32	LReLU	0.4
pool6	3×3	2	8×8×32	-	-
fc7	-	-	1×1×128	LReLU	0.5
fc8	-	-	1×1×5	softmax	-

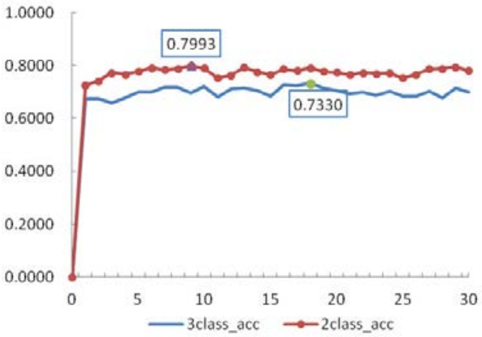


Fig. 5. Evaluation results

5. Implementation of the automatic detector

A detector was created using learned classifier to detect cracked part and chalk letter part from photographs such as Fig. 6. Fig. 6 (a) is a photograph that there are cracks part on coated concrete, while Fig. 6 (b) is a picture that there are cracked part and chalk letter part on non-coated concrete. Cracked part can be seen so clearly with naked eyes in coated concrete. But, non-coated concrete has many stains, so cracked part can't be seen with the naked eyes.

(a) (b)

Fig. 6. Photographs of concrete (a) Coated concrete with cracks; (b) Non-coated concrete with cracks and chalk letters

By raster scan of a constant rectangle on the photograph, the image on the rectangle was put in classifier and classified into cracked part or chalk letter part or others part at any time. A rectangle was displayed in a region where was determined cracked part or chalk letter part on the photograph.

6. Detection results

The result is Fig. 7 that detected cracked part from Fig. 6 (a). As the result has only a little false and missed detection such as blue and orange circles respectively, it can be seen that well detected and said successful. The result is Fig. 8 (a) that detected chalk letter part from Fig. 6 (b). As the result don't have false detection, it can be seen that well detected and said successful, too. The result is Fig. 8 (b) that detected cracked part from Fig. 6 (b). As detector don't recognize stain but cracked part and don't detect cracked part next to the chalk letter part, it can be seen that said fail. Incidentally, calculation time was about 40 seconds.

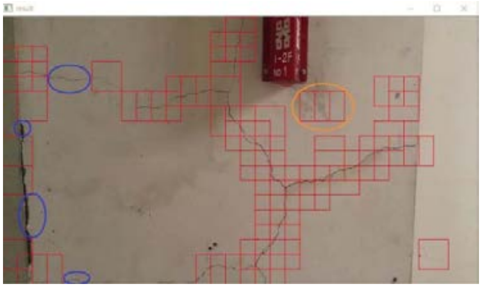
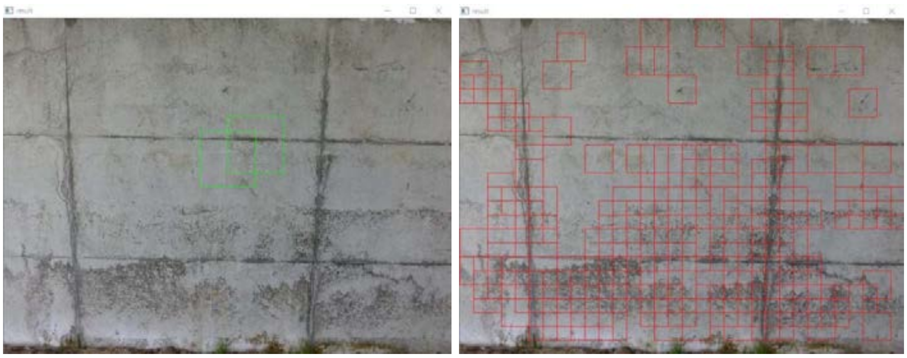


Fig. 7. Detection result from Fig. 6 (a).



(a) (b)

Fig. 8. Detection result from Fig. 6 (b). (a) chalk letters part; (b) Detection of cracked part

7. Discussion

Detection rate of cracked part in concrete with no stains is high, while detection rate in concrete with stains is very low. As rectangle are gathered in parts of the stain, it can be seen that the detector detected stain as crack. For this reason, it is necessary to collect images of stain concrete and make the detector learn them. Also, preprocessing such as reducing bias is necessary as bias of data between the training data is considered to interfere with the learning.

8. Conclusions

This paper presented an automatic detector of cracks in concrete using convolution neural network which is a kind of deep learning. In the case of cracked part detection, cracks in coated concrete was well detected, while cracks in non-coated concrete was not well detected. In the case of chalk letter part detection, chalk letter in non-coated part was well detected. To be able to detect cracks in concrete in any condition is future task of this study.

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