A Fundamental Study on the Application of Convolutional Neural Network for Hammering Sound Test Data of the Deteriorated Concrete

○Yifan YIN*, Yoshimi SONODA**
*Student Member Kyushu University
**Fellow Member Kyushu University

1. Introduction

Recently, amounts of infrastructures are approaching their designed life, thus the number of deteriorated concrete structures is increasing rapidly. In order to apply the proper maintenances, inspections are conducted regularly on concrete structures. The regular inspection is based on visual inspection, and non-destructive inspections for more detailed information on the interior condition. Among non-destructive inspections, hammering sound test using rotary hammer is one of the most popular methods because of its feasibility and low-cost advantages. However, there are several disadvantages of the rotary hammering test. It is highly dependent on the inspector's experiences of deterioration detection, moreover, the data processing for analysis is considered to be not efficient enough. On the other hand, application of artificial intelligence on the maintenance of civil engineering structures is gathering the spotlight. In this study, the objective is to develop an accurate and efficient evaluation method of the concrete structure soundness based on hammering sound test data using the convolutional neural network (CNN).

2. Classification Model

2.1 Experimental Data and Data Processing

Experimental data from rotary hammering test conducted on mortar cuboid with artificial deterioration is used as the learning data to feed the classification model. Details of the experiment is explained as shown in Fig.1, based on 10×10×40 cm mortar cuboid specimen, artificial deterioration using styrofoam was used to simulate deterioration inside concrete structure. There were four different sizes of artificial deteriorations, 2×3×5 cm, 2×5×10 cm, 2×5×15 cm, 2×7×20 cm. The acoustic data was recorded with IC recorder which had a sampling frequency of 44.1 kHz.

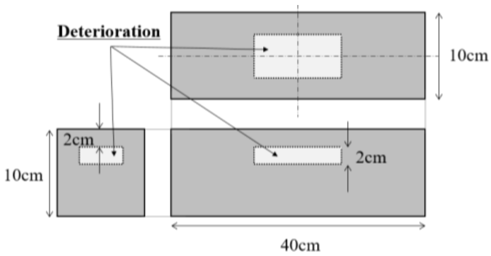

Fig.1 Motar Cuboid

Image of spectrogram from acoustic data, as shown in Fig.2, will be used as the learning data. In a spectrogram, there are three key features of acoustic data. The first feature is the maximum amplitude, it tends to be obviously greater of a deteriorated structure than of a soundness one. The second feature is the time duration which deteriorated structures are also greater than normal ones. Last key feature is the distinct pattern of frequency characteristic which is gained from applying Fourier transform. By using the spectrogram, all these three features can be used as the references to for classification.

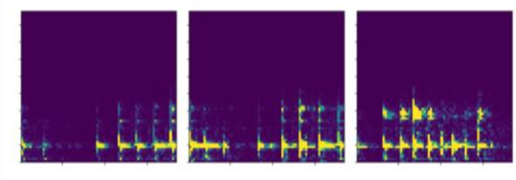
Fig.2 Spectrogram

2.2 CNN Classification Model

The system of classification using convolutional neuron network is as shown the flow chart Fig.3. Input data contains spectrogram generated from the previous procedure, and classification of each spectrogram data as labels. Input data was fed into the convolutional neuron network for deep learning process, it output prediction on classification of the input data. Base on the input labels and the output from classification model, bias and weights are updated by the optimizer. As the learning proceeds, loss function decreases, while the accuracy of prediction increases respectively, as shown in Fig.4, and both tends to be stable. Finally, data that is not used in the learning process will be feed into the classifier model to predict its deterioration class. In this study, 80% of the data prepared are used as learning data, the left 20% are used as validation data. The classifier is tested by validation data, and the final accuracy of validation is 91.3%.

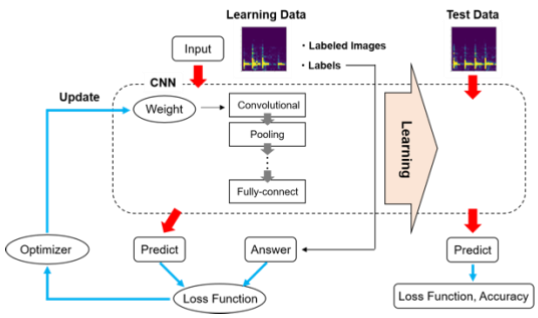

Fig.3 CNN Classification Model

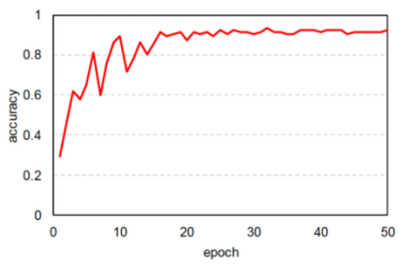

Fig.4 Prediction Accuracy

3. Validation

3.1 Validation on Inspection Data

The CNN model was validated with actual inspection data. The inspection data used in the validation was from rotary hammering inspections of 4 bridges A~D. For each bridge, rotary hammering test was conducted on two intact areas, and two deteriorated areas where the reflected sounds were obviously different from the intact area while the interior conditions were not clarified. Since the interior conditions were not clarified, it is not feasible to classify the deteriorations' sizes. Thus, in this validation, instead of the deteriorations' sizes, the labels were considered as the level of deteriorations, where level 1 stands for normal, and level 2~5 stands for the deterioration size of 2×3×5 cm,2×5×10 cm,2×5×15 cm,2×7×20 cm respectively. Inspection data was converted into spectrogram and then fed into the CNN model for soundness prediction. The results of the predictions were as shown in Table.1. The deteriorated levels of normal areas were correctly predicted as level 1 in 5 inspection points out of a total number of 8. At the same time, for the deteriorated areas, except for one inspection point, the predictions of deteriorated levels of others were all resulted in at least level 2 in average. From this result, it is reasonable to conclude the feasibility of the CNN model on soundness evaluation.

Table.1 Predicted Deteriorated Level

	A	B	C	D
Normal 1	3.4	2.7	1.0	1.0
Normal 2	1.0	3.4	1.0	1.0
Deteriorated 1	3.1	2.0	3.5	2.6
Deteriorated 1	4.3	3.3	2.3	1.4

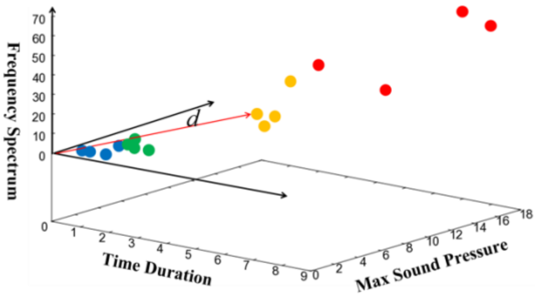

Fig.5 Present investigation method

3.2 Comparison with Present Method

Furthermore, the results were compared to consequences based on a previous study which is to construct a three-dimensional diagram with amplitude ratio, time duration and frequency of hammering sound test data for further validation. As shown in Fig.5, the present method uses the distance from the origin point on the diagram to represent the deterioration level. This method is considered to be able to represent the interior condition of concrete structures. Same data set was used in the evaluation by the present method, the comparison of results from the CNN model and from the present method were as shown in Table.2 and Table 3 seperated by the soundness of bridges. First, regarding the normal structures. 5 of 8 of the normal structures were predicted correctly by the CNN classification model. However, there are three of them predicted as over deteriorated level 2. Comparing to the 3-d diagram method, the distance from origin point of those bridges are also higher than the others. It can be considered that those three points could be closer to be deteriorated. Next, regarding the deteriorated structures. All 8 points were predicted to be higher than deteriorated level 1. In comparison with the 3-d diagram, the distances are all obviously greater than that of the normal structures, which means it can be said that the model successfully detected all deteriorated structures. Moreover, the predicted deteriorated level varies from 1.4 to 4.3 in response to distinct value of distance on the 3-d diagram.

Table.2 Results Comparison - Normal

Location	CNN Model		3-D Diagram	
	Rank	Level	Rank	Distance
B2-N	1	3.4	1	2.8
A1-N	1	3.4	3	1.8
B1-N	3	2.7	2	2.4
D1-N	4	1.0	4	1.5
D2-N	4	1.0	5	1.5
C1-N	4	1.0	6	1.5
C2-N	4	1.0	7	1.4
A2-N	4	1.0	8	1.3

Table.3 Results Comparison - Deterioorated

Location	CNN Model		3-D Diagram	
	Rank	Level	Rank	Distance
A2-D	1	4.3	1	39.7
C1-D	2	3.5	6	18.9
B2-D	3	3.3	5	21.3
A1-D	4	3.1	3	25.5
D1-D	5	2.6	2	26.8
C2-D	6	2.3	4	22.4
B1-D	7	2.0	7	9.6
D2-D	8	1.4	8	8.1

4. Conclusion

In this study, an optimal hammering sound test soundness investigation of concrete structure applying convolutional neuron network was discussed. Firstly, rotary hammering test data was processed to spectrogram and then fed into a CNN model for training. Then the trained CNN model, a classifier of concrete structure soundness, was validated using experimental data. At last, the CNN model was additionally testes with inspection data can compared to previous investigation method. Through this study, the following conclusions could be summarized.

1) The prediction accuracy of the CNN model based on spectrogram of acoustic signal from hammering sound test resulted in 91.3%, which is safe to say that spectrogram could be an appropriate input data for the machine learning process.
2) The prediction of deterioration level by the CNN model showed similar trends as the present investigation method, so the CNN model could be used for actual bridge inspections.