# A FUNDAMENTAL STUDY ON RISK ASSESSMENT BY USING HAMMERING SOUND TEST ON CONCRETE STRUCTURE UNDER REPEATED IMPACT

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## 1. INTRODUCTION

In recent times, an increasing number of concrete peeling accidents is becoming a controversial issue. To avoid accidents and apply proper maintenances, non-destructive inspections are conducted regularly on concrete structures. Among non-destructive inspections, hammering sound test is one of the most popular methods because of its feasibility and low-cost advantages. However, hammering sound test is highly dependent on the inspector's experiences of defect detection, moreover, the standard to evaluate the degree of defect is remaining controversial. Therefore, a stable evaluation standard of defect degree on hammering sound test is required. 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 utilizing the convolutional neuron network (CNN).

## 2. EXPERIMENT

### 2.1 Specimen

In this experiment, a 10 × 30 × 30 cm mortar specimen as shown in Fig. 1 was made to conduct the repeated impact test. Table 1 shows the composition of mortar. Here, the specimen was designed with an artificial defect. The dimensions of the artificial defect were 51 x 51 mm, and the thickness was 6 mm, which enabled a cavity inside the specimen of 50 x 50 x 5 mm. In addition, the burial position of the artificial defect was 50 mm from the top surface of the specimen. The specimen was cured for 28 days by using wet sheet curing.

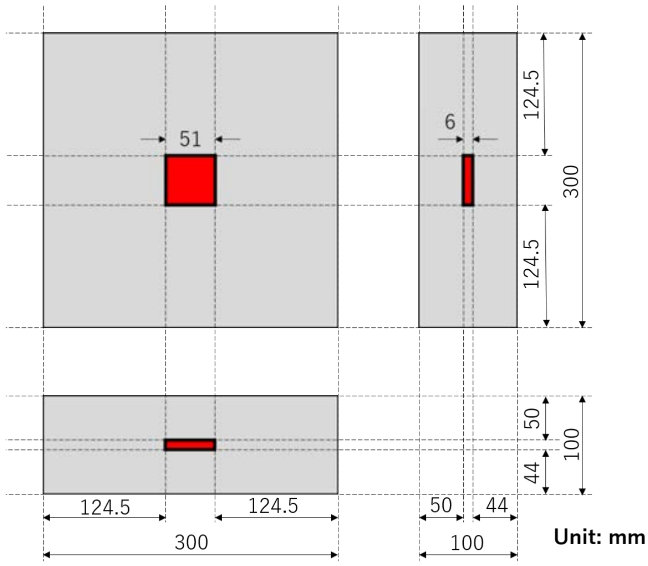


Fig.1 Mortar Specimen

Table 1 Composition of Mortar Specimen

| W/C | S/C | Unit Quantity(kg/m3) | | |
|---|---|---|---|---|
| | | W | C | S |
| 0.5 | 3.5 | 227 | 454 | 1588 |

### 2.2 Repeated Impact

Using the prepared test piece, a repeated impact test was performed to observe the change in the sound characteristics of the hammering sound test when the inside of the mortar test piece was damaged. The test piece was set in a two-sided support state, and a 6.115 kg iron ball was repeatedly used for impact. An iron ball was freely dropped 40 times at a height of 150 cm at the center of the specimen, and a hammering sound test was performed after each impact, and a sound pressure time history was recorded.

## 3. CLASSIFICATION MODEL

### 3.1 Input Data

The images of spectrograms that were converted from sound pressure waveforms, as shown in Fig.2, was used as the input data for machine learning process. In a spectrogram, there are three key features of hammering sound test data. The first feature is the maximum amplitude, it tends to be obviously greater as of a defect structure than of a soundness one. The second feature is the time duration which defect structures are also greater than

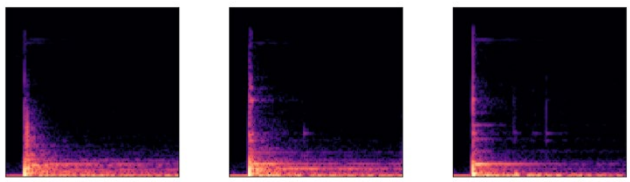

Fig.2 Spectrogram

Table 2 Labels of Defect Degree

| Times of Impact | 0~10 | 11~20 | 21~30 | 31~40 |
|---|---|---|---|---|
| Defect Level | Level 1 | Level 2 | Level 3 | Level 4 |

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the normal ones. The last key feature is the distinct pattern of frequency characteristic. By using the spectrogram, all these three features can be used as the references to for classification. In this study, the data was divided into 4 labels respectively to the times of impact simulating the degree of defect, as shown in Table 2.

### 3.2 CNN Classification Model

The structure of CNN classification model is shown as Fig.3. Input data contains spectrogram generated from the previous procedure, and degree of defect of each spectrogram data as labels. Inputs were fed into CNN model, and base on the input labels and the output of labels from classification model, bias and weights were updated by an optimizer. As the learning proceeded, loss function decreased, while the accuracy of prediction increased respectively, as shown in Fig.4. Finally, data that was not used in the learning process was supplied to the classifier model to predict its defect class. In this study, 80% of the data prepared were used as learning data, and 20% of the data were used as test data. The classifier was tested by test data to detect the defect level of experimental data, and the final accuracy was 88.81%.

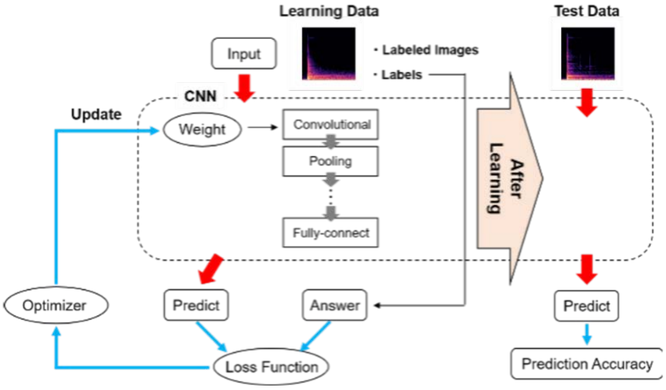


Fig.3 CNN Classification Model

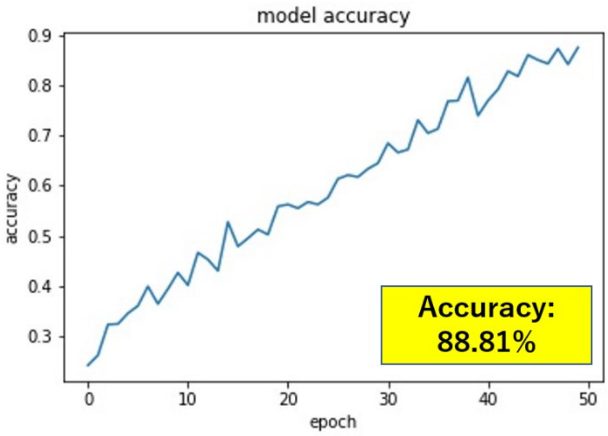


Fig.4 Model Accuracy

### 3.3 Validation

In order to further verify the accuracy of the CNN classification model that had been developed, 20 data from each label were preserved as validation data and were feed into the CNN classification model to predict the degree of defect. The results of the predictions are shown as Table 3. For the first label, 18 among 20 were accurately predicted as level 1. As for level 2, 5 of the validation data were predicted as level one, and the other 15 data were accurately predicted. For level 3, 14 data were correctly predicted while the other 6 were predicted as level 2. Finally, in the prediction of level 4, all 20 data were correctly predicted and classified into label 4. From these results, the initial and final stages of defects can be identified relatively accurately, but the differences between the two stages of moderate defects (level 2 and level 3) cannot be clearly classified.

Table. 3 Validation Results

| | Level1 | Level2 | Level3 | Level4 | Accuracy |
|---|---|---|---|---|---|
| Level1 | 18 | 0 | 0 | 2 | 90% |
| Level2 | 5 | 15 | 0 | 0 | 75% |
| Level3 | 0 | 6 | 14 | 0 | 70% |
| Level4 | 0 | 0 | 0 | 20 | 100% |

## 4. DISCUSSION

In order to develop a reliable evaluation system of concrete structure soundness, repeated impact test of a mortar specimen was conducted. Although, this test did not result in any floats nor peeling of the specimen due to the lack of the magnitude of load, we tried to estimate the damage condition that gradually progresses in the repeated impact test. In this experiment, hammering sound data of repeated impact test were classified into 4 levels of damage and fed into a CNN classification model for training. After that, the trained CNN classification model was used to predict the degree of damage on the hammering sounds data that is not used for learning. As a result, it is confirmed that an overall accuracy of 83.75%, which proved that the CNN classification model has the potential to accurately predict the degree of defect of concrete structure. In the future, we would like to continue this test and improve the accuracy of the CNN model.

## REFERENCES

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