Development of AI for Evaluating the Quality of Concrete Surface Roughness

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1. Introduction

Concrete structures inevitably have construction joints. In structures requiring watertightness, such as dams and waterways, water leakage from construction joints is a critical issue. Therefore, in the construction of concrete dams, proper treatment of construction joints is essential. This treatment involves removing laitance, poor-quality concrete, and loose aggregates from the upper surface of the underlying concrete before the next layer is cast.

In previous studies, an investigation was conducted to determine whether the exposure state of coarse aggregates could be used to evaluate proper construction joint treatment. As part of this investigation, four exposure conditions were reproduced by adjusting the amount of laitance removal (Fig. 1). This was followed by shear tests and measurements of surface roughness. The results demonstrated that assessing the surface roughness of coarse aggregates after laitance removal enables proper execution of construction joints.

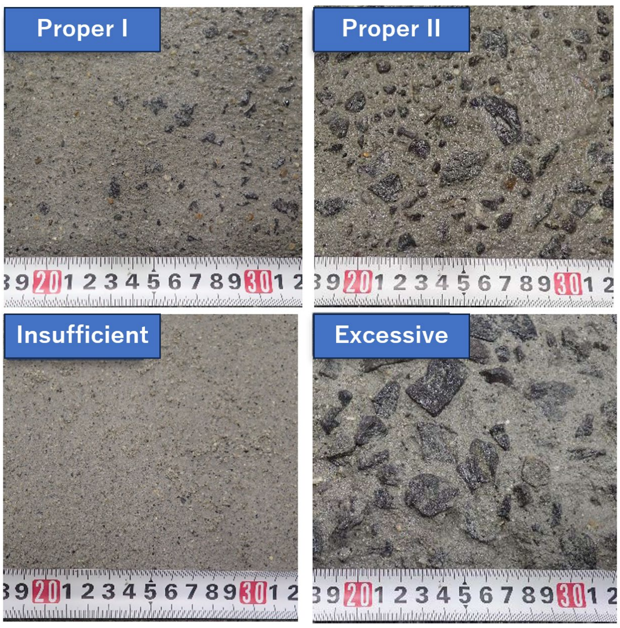

Fig. 1. Examples of Criteria for Evaluating Concrete Surface Conditions

The evaluation of concrete surfaces is currently performed through visual inspection by skilled technicians. However, the construction of large-scale structures requires the assessment of extensive surface areas, which is time-consuming. Additionally, challenges such as the aging population and the difficulty of passing down technical expertise highlight the need for evaluation methods that do not rely on individual skilled technicians. To address these issues, an AI system was developed to assess the quality of laitance treatment simply by capturing images of concrete surfaces (Fig. 2). This system enables large-scale evaluations to be conducted in a short amount of time without the presence of skilled technicians, thereby improving productivity.

Fig. 2. Utilizing the Prototype Inspection System

2. AI Prototype for Evaluating Proper Construction Joint Treatment Conditions

In this study, two AI models were evaluated. The first is an AI model designed to classify the four exposure conditions shown in Fig. 1, and the second is an AI model that quantitatively evaluates the surface roughness of concrete. This section will first explain the AI model for classifying the four exposure conditions.

The AI model for classifying exposure conditions was constructed using a convolutional neural network (CNN), which is commonly employed in image recognition tasks. This model outputs the predicted probability of the input image belonging to each of the four exposure conditions. The structure of the AI model used in this study is shown in Fig. 3, where the numbers within the diagram indicate the outputs of each layer of the network.

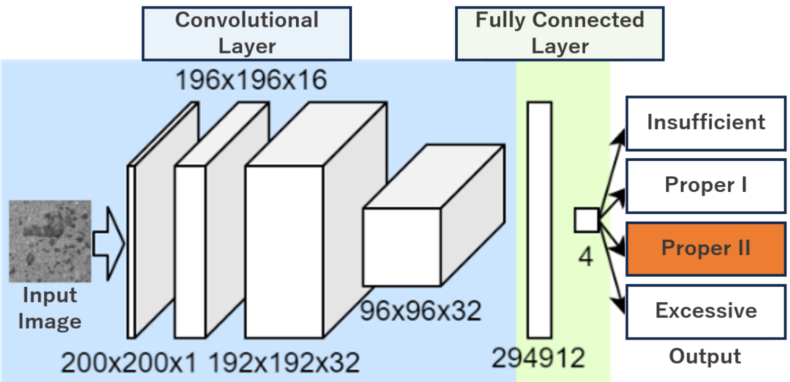

Fig. 3. AI Model for Classifying Exposure Conditions

To validate the accuracy of the AI model, 400 images were captured from four concrete test specimens. Of these, 50 images from each exposure condition—200 images in total—were used as test data to validate accuracy, while the remaining 200 images were used for training. The results of the model evaluation are summarized in Table 1.

Table 1. Classification Results of Exposure Conditions Using an AI Model

	Insufficient	Proper I	Proper II	Excessive
Accuracy	100.0%	98.0%	100.0%	98.0%

The model achieved an exceptionally high accuracy rate of over 98%. These results indicate that the CNN-based AI model can accurately recognize the laitance treatment conditions when using image data captured under consistent conditions, such as the dataset prepared for this study.

The method for quantitatively evaluating exposure conditions also employs an AI model based on a CNN, similar to previous validations. The AI model used in this study is shown in Fig. 4.

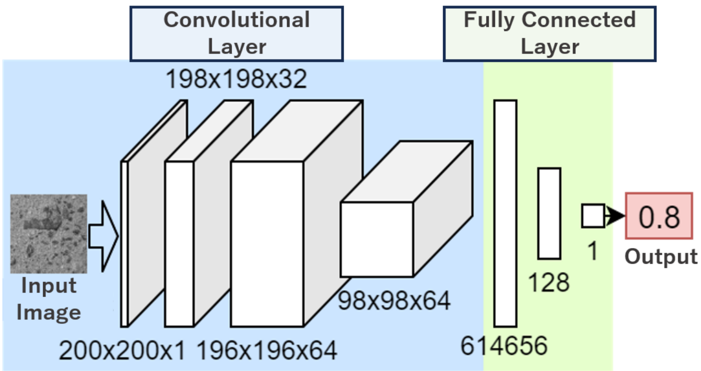

Fig. 4. AI Model for Quantitatively Evaluating Exposure Conditions

In this validation, the standard deviation of the height variation on the concrete surface was used as an indicator to represent surface roughness. The purpose of this study was to output surface roughness as a quantitative value based solely on images. To achieve this, a prototype AI model was developed to output the standard deviation of Z-values as the evaluation metric.

In this validation, to train the AI model to learn quantitative surface roughness, a dataset was constructed by linking the collected image data with the roughness values of the captured area. A 3D scanner with a depth resolution of 0.5 mm was used to accurately measure the surface roughness.

The depth images of the surfaces obtained from each test specimen are shown in Fig. 5. In the images, areas with higher brightness indicate higher Z-values, while areas with lower brightness indicate lower Z-values. As observed in the figure, the Insufficient condition shows minimal surface undulation, while Proper I and Proper II show appropriate exposure of coarse aggregates. In contrast, the Excessive condition shows significant undulations across the entire surface. For better visibility, the images presented in this paper have enhanced contrast.

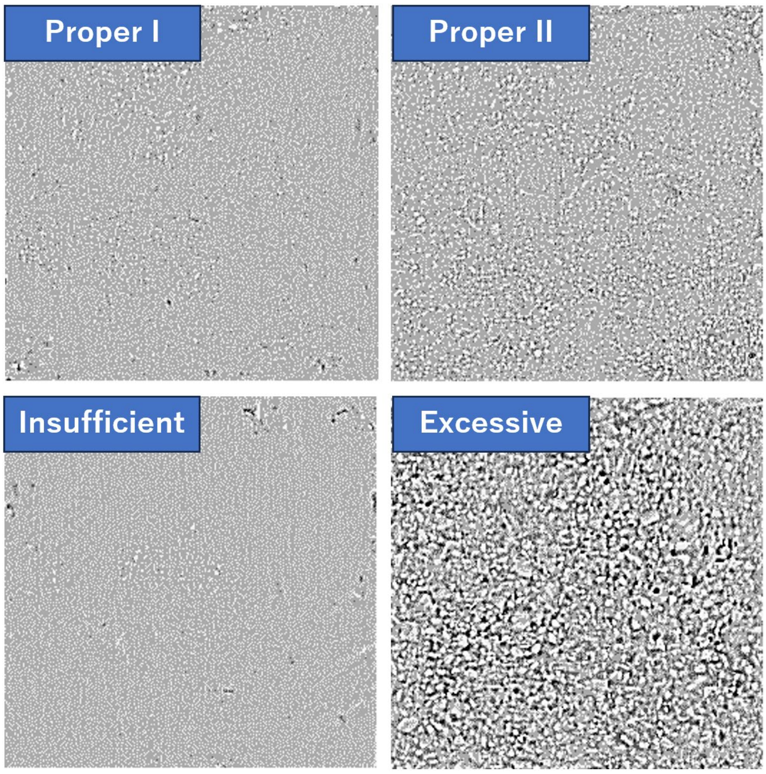

Fig. 5. Depth Images of the Surface Acquired Using a 3D Scanner

Fig. 6 shows the standard deviation of Z-values for the entire surface of each test specimen. Looking at the figure, Insufficient, Excessive, and Proper I and Proper II conditions can be distinguished based on their surface roughness.

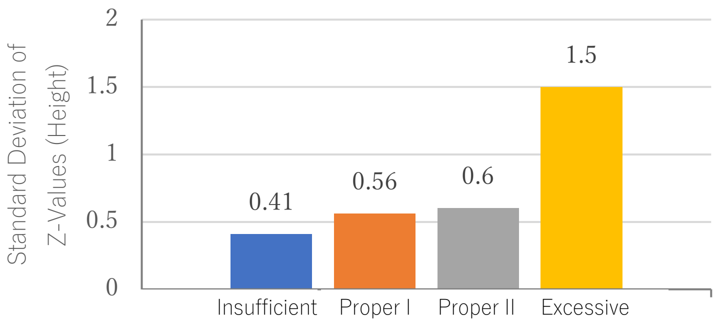

Fig. 6. Standard Deviation of Z-Values
for the Entire Surface of Each Exposure Condition Test Specimen

For the validation of this AI model, a total of 400 images were captured for the four exposure condition test specimens. Of these, 10 images from each exposure condition—40 images in total—were used to evaluate accuracy, while the remaining 360 images were used for training. During training, data augmentation was applied to expand the dataset as we aimed to achieve high-accuracy roughness evaluations.

Fig. 7 shows the comparison between the measured values and the predicted values from the AI model. Although there were significant differences between the measured and predicted values in many cases, the overall trends in the predicted values aligned with those observed in the measurements obtained using the 3D scanner.

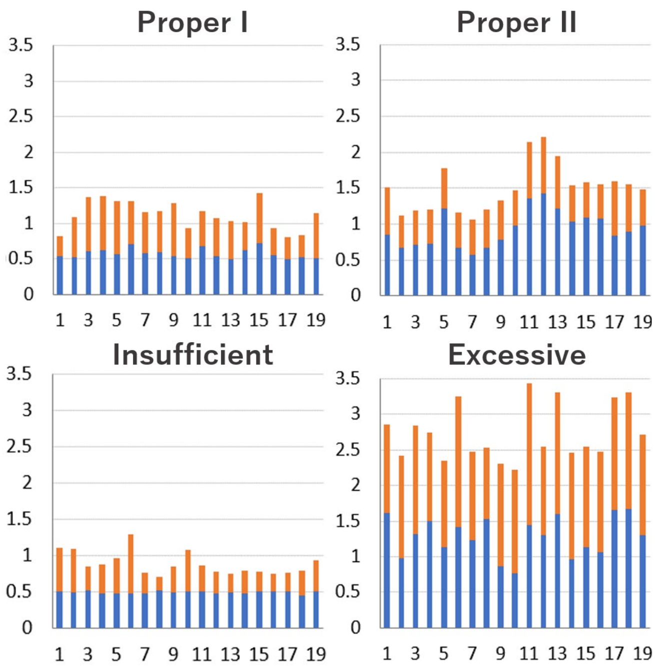

Fig. 7. Comparison of Predicted and Measured Values
(Y-Axis: Standard Deviation of Z-Values (Blue: Predicted, Orange: Measured),
X-Axis: Image ID)

In the case of Insufficient and Proper I conditions, there were instances where the measured values and predicted values differed significantly. However, for conditions with larger measured values, such as Proper II and Excessive, the predicted values tended to closely follow the measured values. Additionally, the average predicted values for each construction condition followed the same trend as the measured values, with Insufficient < Proper I < Proper II < Excessive.

The objectives of this validation were to determine whether, under ideal conditions using test specimens, (1) the decision-making criteria of skilled workers could be mimicked, and (2) surface roughness could be quantitatively evaluated. Based on the results, it was concluded that both objectives are achievable.

3. Conclusion

This study examined a method for evaluating concrete surfaces using AI as a countermeasure against the declining number of skilled technicians due to the aging population. The investigation focused on two key objectives:

(1) Determining whether AI can replicate the classification of construction conditions by skilled technicians.
(2) Assessing whether AI trained on surface roughness data obtained from a 3D scanner can quantitatively evaluate roughness using images alone.

The results for objective (1) were favorable, demonstrating that the AI was able to accurately reproduce classifications made by skilled technicians. For objective (2), while the AI successfully predicted trends in surface roughness during controlled experiments, the results from on-site experiments indicated room for improvement. It was determined that accurate predictions require larger datasets and more standardized imaging conditions.

Moving forward, we plan to continue on-site validations to gather additional training data, improve model accuracy, and work towards practical implementation in real-world construction environments.