An Attempt to Introduce Artificial Intelligence Technology for Classification of Drilling Patterns

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1. Introduction

In a mountain tunnel construction, the automation of explosives handling near the face is required from the safety point of view. Currently, determining the blasting pattern including allocation of holes and explosive volume is designed before the excavation based on each ground class, and then adjusted and modified as needed based on the empirical judgment of skilled miner for blasting sometimes called as drill-master. However, with the decline of skilled workers, maintaining the quality of blasting excavation has become a challenge, and there is a need to quantify these judgment criteria. With the spread of computerized jumbos, it is no longer possible to rely on the intuition of skilled miners, and there is a need for a system to automate pattern modifications and changes. Currently, it is expected to achieve complete automation of blasting patterns by AI technology, but the success of AI projects requires verifying a simple process for introducing AI[1)]. In this study, we discuss the potential for introducing AI regarding classifying drilling patterns, as an example.

Firstly, in the context of the need to estimate drilling patterns and the amount of explosive, this study attempted to classify drilling patterns. Specifically, we examined the possibility of classifying drilling patterns using convolutional neural network (hereinafter, referred to as "CNN"), a type of machine learning, by face images as training and test data. To accurately analyze using machine learning, the amount of dataset is crucial. However, in actual construction sites, it is often insufficient. In such cases, data augmentation can be performed by applying processes such as flipping horizontally and vertically or grayscale conversion to images. We analyzed how these processes affect the accuracy of the classification of drilling patterns using face images.

２. Methodology

(1) Classification of drilling patterns

The drilling patterns applied in a tunnel were classified into three types by the author's visual inspection: 1) drilled through the entire face 2) no drilling in the center of the face, and 3) the other. Examples of face images for each pattern are shown in Figures 1 to 3. There are 159 images in total for each pattern, indicating a bias in the amounts of faces. In actual face pattern analysis, detailed analysis focusing on Pattern (1) is necessary, but in this study, we attempted to examine the classification by geological grouping.

(2) Analysis by CNN model

A neural network that incorporates convolutional layer and pooling layer in the hidden layer is the CNN. CNN is a method that has achieved results mainly in the field of image recognition. The CNN model used in this study consists of four convolutional layers, four pooling layers, and two fully connected layers. The analysis procedure involved dividing the face images into 8:2 ratios for each pattern as the training and test data, respectively. The model was trained by the training data and its performance was evaluated by test data. To consider the variability of the results, we conducted the analysis 20 times.

Keywords: mountain tunnel, rock blasting, convolutional neural network, tunnel face, drilling pattern
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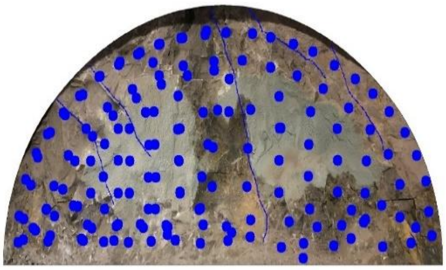

Fig. 1. drilled through the entire face (Pattern 1)

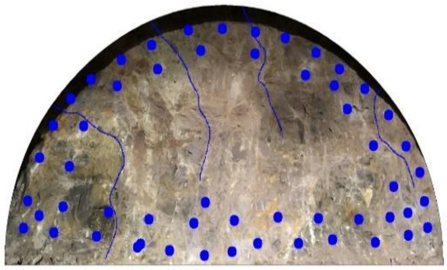

Fig. 2. no drilling in the center of the face (Pattern 2)

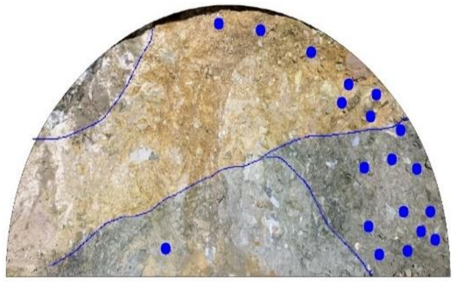

Fig. 3. the other (Pattern 3)

3. Results and Discussion

The analysis was conducted using a total of 159 datasets, and average of accuracy is 0.67. However, the model's output results were mostly Pattern 1. One of main reasons was expected to be the bias in the amounts of faces. Therefore, 14 pieces of data were randomly extracted from each pattern, resulting in a total of 42 datasets. The results of the analysis using this dataset are shown in Figure 4, with an average accuracy of about 0.37. By making the amounts of face images for each pattern equal, the output results no longer biased toward Pattern 1. However, due to the significant reduction in the amounts of faces to make the amounts of face images in each pattern equal, the training did not progress much, and the accuracy was low and unstable. Therefore, to increase the number of data, the images of Pattern 3 were subjected to left-right and up-down flipping, grayscale processing, and the number of data was increased up to 112. In addition, the images of Pattern 2 were subjected to left-right and up-down flipping, and the number of data was increased up to 124. And, 112 pieces of data were randomly extracted from each pattern, resulting in a total of 336 datasets. The results of the analysis using this dataset are shown in Figure 5, with an average accuracy of about 0.70 and no bias in the output results. Moreover, the stability of accuracy has improved. This result showed that even if images subjected to flipping or grayscale processing are added to the training data only in specific classification patterns, the accuracy improves. Therefore, it is possible to use CNN by increasing the amounts of faces through data augmentation, even if the number of usable face images is small or the classification pattern is biased.

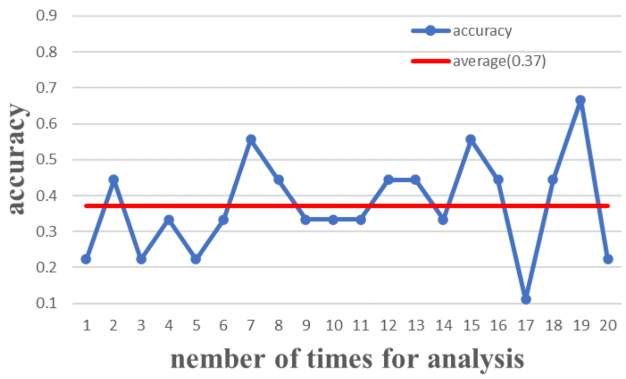

Fig. 4. The results of the analysis using 42 datasets

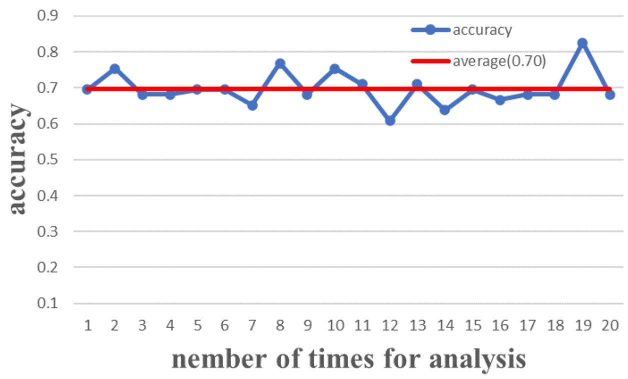

Fig. 5. The results of the analysis using 336 datasets

4. Future Outlook

In the future, we will work on methods such as adding face images from other tunnels as learning data and transfer learning using models trained with images other than faces. In addition, we will consider the fusion of image data and numerical data (for example, Measurement While Drilling).

References

1) Shinichi K. (2020). Acquisition of New Competitive Advantage by Introducing and Using AI at the Manufacturing Enterprises, The Surface Finishing Society of Japan, 71(7), 432-441.