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Deep learning based classification model of rock mass based on RMR of tunnel face

Modèle de classification basé sur l'apprentissage en profondeur de la masse rocheuse basé sur le RMR de la face du tunnel

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ABSTRACT: The determination of appropriate support patterns using the geological surveys at the design stage and interpretation of rock conditions can prevent tunnel collapse and rock falling accidents during tunnel excavation. The rock mass rating (RMR) method for characterizing rock structure requires time and skilled techniques to observe the orientation, length, and spacing of rock joints exposed to the tunnel face. The convolutional neural network (CNN), based on a deep artificial neural network composed of multiple layers of convolution and pooling, shows outstanding performance even in complex images. In this study, a deep learning-based model is developed to classify rock grades by image-based tunnel face analysis. The model constructed using transfer learning achieved the effective classification performance even though the number of tunnel face images was not sufficient. It is conjectured that the accumulation of tunnel face images with additional tunnel excavation sites can not only improve the generalized performance of the classification model but also develop it into a real-time rock mass classification method.

RÉSUMÉ: La détermination de modèles de support appropriés à l'aide des études géologiques au stade de la conception et de l'interprétation des conditions de la roche peut empêcher l'effondrement du tunnel et les accidents de chute de pierres lors de l'excavation du tunnel. La méthode d'évaluation de la masse rocheuse (RMR) pour caractériser la structure rocheuse nécessite du temps et des techniques qualifiées pour observer l'orientation, la longueur et l'espacement des joints de roche exposés à la face du tunnel. Le réseau neuronal convolutif (CNN), basé sur un réseau neuronal artificiel profond composé de plusieurs couches de convolution et de mise en commun, affiche des performances exceptionnelles même dans des images complexes. Dans cette étude, un modèle basé sur l'apprentissage en profondeur est développé pour classer les grades de roche par une analyse de la face du tunnel basée sur l'image. Le modèle construit à l'aide de l'apprentissage par transfert a atteint les performances de classification efficaces même si le nombre d'images de face de tunnel n'était pas suffisant. On suppose que l'accumulation d'images de façade de tunnel avec des sites d'excavation de tunnel supplémentaires peut non seulement améliorer les performances généralisées du modèle de classification, mais aussi le développer en une méthode de classification de masse rocheuse en temps réel.

KEYWORDS: Deep learning, convolutional neural network, rock mass rating, rock mass classification, tunnel face image

1 INTRODUCTION

Complex geotechnical material has a high spatial uncertainty while the predictability seems low, therefore the necessity of technical alternatives to prevent safety accidents in large-scale construction projects increases. In particular, during tunnel construction, it is necessary to determine an appropriate support pattern through observation of the tunnel face during construction to minimize the loss of life and property due to tunnel collapse accidents in hazard sections such as rock formation change sections, relaxation, and fault fractured zones.

The determination of the rock mass classes of the tunnel section is directly related to the selection of support patterns, and representative rock mass classification methods include the rock mass rating (RMR) system and the Q-system. The RMR classification evaluates the rock mass condition in detail according to six elements and classifies the rock mass into five grades using the sum of each score (Bieniawski, 1989). The total score is distributed between 0 and 100, and the higher the value of RMR the better the rock mass conditions from the engineering point of view. The six elements of the RMR classification are as follows, and the state of the rock mass is classified according to the value of RMR as shown in Table 1; the unconfined compressive strength of the intact rock, the rock quality designation (RQD), the spacing of the discontinuities, the condition of the discontinuities, the groundwater conditions, and

the correction for the orientation of discontinuities. The Q-system is a method to perform quantitative rock classification based on the following six variables, considering the spacing and conditions of the discontinuities more important than the orientation of the discontinuities (Barton et al., 1974); the rock quality designation (RQD), number of joint sets, the roughness of the most unfavorable joint, degree of alteration of filling along the weakest joint, water inflow, and stress reduction factor (SRF). Since it is difficult to grasp all the ground characteristics through surveying and site investigation at the design step, it is needed to perform the identification of the rock characteristics and reinforcement through real-time rock classification based on face mapping of the tunnel face exposed during construction. Nevertheless, observation of the tunnel face requires skilled technology and a lot of time, and the acquired data has a limit in which the subjectivity of field experts is reflected.

Table 1. Description of rock mass quality based on RMR.

	Rating				
RMR	81-100	61-80	41-60	21-40	≤20
Class	I	II	III	IV	V
Rock quality	Very good	Good	Fair	Poor	Very poor

The recent image recognition technology based on artificial intelligence (AI) has developed to a level that imitates human visual recognition ability. Also, the development of deep learning-based autonomous driving technology and the smart city establishment, and active introduction to the medical field as auxiliary means to increase the accuracy of diagnosis are being made. This study aims to develop a technology to rapidly analyze rock features from tunnel face images by using a convolutional neural network (CNN) of deep learning method that effectively performs the object recognition through extraction and combination of features such as edges, corners, and lines within images.

2 MATERIALS AND METHODS

2.1 Dataset preparation

Tunnel face images were taken with a mobile phone at a total of 10 different tunnel sites, and face mapping data were manually recorded by experts at the site for rock mass classification using the RMR method. A total of 3318 images of the tunnel face were obtained, and each image was labeled with five rock mass classes. Figure 1 shows representative tunnel face images according to the rock mass class. The input image for model training was cropped to remove unwanted objects or irrelevant noise and resized to a fixed size of 400×800.



Figure 1. Typical tunnel face images by rock mass class and the corresponding value of RMR.

A total of 2654 images were used for training the classification model (80% of the total data) and the data augmentation technique was applied only to the training data to achieve effective rock mass classification performance for an insufficient number of training data. Since the image includes the tunnel lining shape like a half-circle, only data augmentation by the left and right reverse (i.e., mirror mode) is allowed, and the number of original data is doubled. In addition, 332 validation images (10% of the total data) were separately prepared to prevent overfitting of the model and adjust the hyper-parameters of the model to achieve optimal performance. Another 332 test images (10% of the total data) not participated in model training were used to evaluate the classification accuracy of the trained model. The dataset used for each step was randomly selected from the total data, and the split ratio for each rock mass class was equally applied. Table 2 shows that the number of images for each rock mass class included in each dataset.

Table 2. Number of data by rock classification criteria for training, validation, and test for the deep learning-based rock classification model

	Class				
	I	II	III	IV	V
Training	9	454	1043	1038	112
Validation	2	56	130	129	14
Test	2	56	130	129	14

2.2 Rock mass classification model

The CNN consists of several convolutional layers and pooling layers, and the quality of features extracted from input images varies depending on the structural arrangement of the layers or the algorithm selected and applied for learning optimization. The convolution filter slides the entire input image while moving by a specified interval called stride, and the convolution operation between the input image and the filter generates a feature map. Therefore, since the values in the convolution filter are shared weights across the input data, it has advantages of training time and computation memory by using fewer parameters compared to conventional artificial neural networks such as a fully connected layer that connects every pixel of the input data with the next nodes. Also, CNN learns low-level features such as edge and curve at layers close to the input, and as the layer deepens, they can learn the spatial hierarchy of patterns by recognizing high-level features such as texture and object parts. This causes the output layer of CNN to perform complex inference, such as classification of input data, recognition, or detection of objects.

Through a contest called ImageNet Large Scale Visual Recognition Challenge (ILSVRC), CNN models with outstanding image recognition and classification performance are selected and released annually. It is possible to utilize the parameter weights of the pre-trained model from the ImageNet dataset consisting of 14 million different types of images and 1000 classes by transfer learning. The VGG network series which is simple and intuitively structured, and convenient to transform was used as the base model of the feature extractor in this study (Simonyan and Zisserman, 2015). In consideration of the appropriate model may vary depending on the problem to be solved and the type of input data, the classification performance was compared using models with different depths (i.e., VGG16 and VGG19). In addition, the classification performance for models with added batch normalization layers was verified to reduce learning instability due to the distribution of inputs changing as the layers are deepens (i.e., VGG16 and VGG16 with batch normalization, VGG19 and VGG19 with batch normalization). The classifier was constructed by connecting 4 fully connected layers to the image feature extractor composed of the VGG network series and connected the Softmax layer as the last activation function so that it leads to classifying into 5 rock mass classes from the extracted features of the tunnel face image.

3 RESULTS AND DISCUSSION

3.1 Training experiment with hyper-parameter adjustment

To implement the pre-trained CNN model to each own problem, re-training through fine-tuning of model weights should be performed (Chollet, 2018). Batch size, which affects learning speed and stability, is a variable that is dominantly determined on computation power, so that batch size 8, the maximum usable size in this study, was applied. The direction and size of model weight adjustment for training are determined by the types of loss function, optimizer, and learning rate. In the image classification

task, a cross-entropy loss is used because the loss function is defined as whether the label predicted by the matches the target actual label. The optimizer and learning rate generally select efficient values without overfitting the model to the training data through observation of training and validation loss during model training. The training loss acquired at every epoch is indicated by a solid line according to the types of the optimizer (i.e., Stochastic Gradient Descent (SGD) and Adam) and learning rate, and the validation loss is expressed by a dotted line as shown in Figure 2. The validation loss of the model using the Adam optimizer shows the severe overfitting of the model, and the SGD optimizer shows fast and stable convergence of loss when the learning rate is 1E-04.

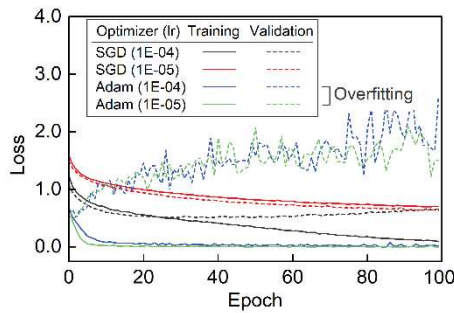


Figure 2. Comparison of training and validation loss of rock mass classification model by optimizer and learning rate.

3.2 Classification results

To maximize the effect of training of a deep learning-based CNN model, securing a sufficient number of data is most important, thus data augmentation technology is mainly used. Table 3 shows the difference in model classification accuracy before and after data augmentation for 80% of the total data split for training. To confirm the effect of data augmentation, other variables were fixed as follows: VGG19 model with batch normalization layers and SGD optimizer with 1E-04 of learning rate. According to the number of data for each rock mass class mentioned in Table 2 above, it can be inferred that the classification accuracy is underestimated because the number of tunnel face images in Class I is too small. Therefore, the classification accuracy for the test data except for the tunnel face with Class I is also shown. The model trained with data doubled by data augmentation showed remarkably excellent rock mass classification accuracy as 84.64%, and a slight increase in classification accuracy was observed when Class I was excluded.

Table 3. Rock mass classification accuracy results by data augmentation.

		Classification results	
		Accuracy [%]	Accuracy excluding Class I [%]
Data augmentation	Before (2654)	77.71	78.18
	After (5308)	84.64	85.15

The VGG network set as the backbone network of the feature extractor uses the same size of 3x3 convolution filters for all convolutional layers. Comparing the two results using VGG16 and VGG19 as backbone networks, only the effect of depth change of CNN on classification performance can be confirmed. Because the conventional VGG network does not include a batch normalization layer, if the data distribution is rescaled to an extremely narrow range while the input image is passed through the convolutional layers, so there is a limitation in that proper

learning not be performed. Therefore, the effect of the batch normalization layer was proved in the classification problem in this study by calculated the accuracy of rock mass classification using models that placed batch normalization layers in the middle of the conventional VGG networks as a feature extractor. The loss of the two models without batch normalization converges quickly, but the rebound of the validation loss was observed so that the early stopping algorithm for the purpose of preventing overfitting was activated (Figure 3). In the case of two models with batch normalization layers, the validation loss also converges along with the training loss that gradually decreases.

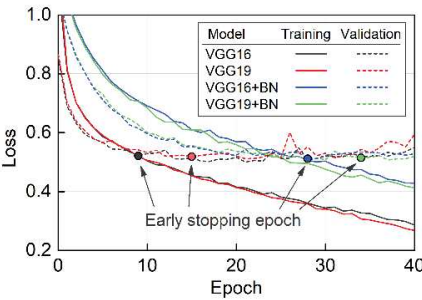


Figure 3. Comparison of training and validation loss of rock mass classification model by the depth of CNN model and application of batch normalization layer.

The classification accuracy of each model by hyper-parameter adjustment to optimize the learning process and produce the best results is shown in Table 4. All of the classification accuracies were measured on separated test data in advance, and the results are for the final models determined by early stopping which terminates training early before model overfits.

It can be seen that the case of using SGD as the optimizer performs better class prediction than the case of applying Adam, and at the same time, the classification accuracy can be improved most effectively when using the learning rate of 1E-04. In the results of four different models comparing the depth of the CNN model and the appropriateness of applying regularization during training by batch normalization, it is confirmed that using the batch normalization layers with the conventional VGG19 network shows the best performance. As previously speculated, the classification accuracy for test data except for Class I data is always higher than when all classes are included.

Table 4. Rock mass classification accuracy results by types of optimizer and learning rate, and CNN model.

		Classification results	
		Accuracy [%]	Accuracy excluding Class I [%]
Optimizer (learning rate)	SGD (1E-04)	84.64	85.15
	SGD (1E-05)	79.22	79.70
	Adam (1E-04)	78.31	78.79
	Adam (1E-05)	74.70	75.15
Model	VGG16	81.63	82.12
	VGG19	82.23	82.73
	VGG16+BN	84.04	84.55
	VGG19+BN	84.64	85.15

Figure 4 shows the confusion matrix used as a classification model performance evaluation indicator for the model that

achieved the highest classification accuracy. The confusion matrix tabulates the number or probability that the targeted actual class and the class predicted by the model match. Since there are only two images of Class 1 of the tunnel face included in the test dataset, representing the prediction results for Class 1 as a probability is meaningless. Therefore, the results for the remaining four rock mass classes are expressed as color gradients with probability. Compared to Class 2, 3, and 4, which contain 50 to 100 or more, the classification result for a small number of data Class 5 also shows a relatively low accuracy of 64.3%. For all of the tunnel face images of Class 2, 3, and 4, it showed outstanding prediction accuracy of over 84%. Also, it is confirmed through the diagonal matrix in Figure 4 that the misclassified cases were also classified into an adjacent class.

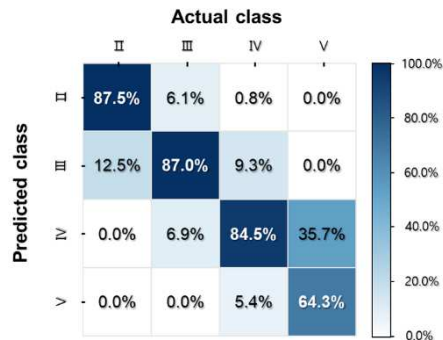


Figure 4. Confusion matrix for the performance evaluation of the rock mass classification model.

4 CONCLUSIONS

This study developed a model that classifies the tunnel face images into 5 rock mass classes using the deep learning technique. The pre-trained VGG network series were used as the backbone networks of the feature extractors, and rock mass was classified with the highest predictive accuracy when batch normalization layers were applied to the conventional VGG19 network. Data augmentation by the left and right reverse of tunnel face images effectively improves classification accuracy by doubling the training data during model training. A tendency to always predict adjacent classes has been observed even when rock mass classes are incorrectly predicted, so it is speculated to help determine the support patterns by rock mass classification during tunnel construction. Also, it can be expected to be utilized as a real-time rock mass classification method by reducing subjective evaluation by experts and the evaluation time of rock characteristics and through more data accumulation.

5 ACKNOWLEDGEMENTS

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