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# Image-based uniaxial rock strength prediction using Deep Learning towards excavation

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## ABSTRACT

Uniaxial compressive strength (UCS) is an important property of rocks that has a wide number of applications, and it has been included in rock mass assessment methods such as RMR and Q System. However, typical rock preparation and testing for UCS is time consuming and costly. In this study, we present an approach for UCS prediction using rock images through Deep Learning, as an initial step on the better and efficient characterization of rock mass during tunnel excavation. For this, we implemented a ResNet and an Inception architecture models for training using multiple rock images and their corresponding USC values. The results indicate an 82% of correlation coefficient for the inception model. Finally, we discuss the possible implications of this approach to provide more decision making aid tools during tunnel excavation.

## 1. INTRODUCTION

In order to prevent possible collapse accidents during tunnel construction, the evaluation of the excavation surface during tunnel construction is an important step, and the appropriate excavation method and supporting method must be determined deliberately. The most widely used rock mass ratings methods are the Rock Mass Rating (RMR) and the Q-System. The factors required by the RMR method include uniaxial compressive strength (UCS), rock quality index (RQD), discontinuity spacing, state of discontinuities, direction of discontinuities, and groundwater (Bieniawski, 1989). On the other hand, the Q-system uses the rock quality index (RQD), the number of joint groups ($J_n$), the roughness of the joint surface ($J_r$), the degree of deterioration of the joint surface

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($J_a$), the groundwater reduction coefficient in the joint ($J_w$), the stress reduction coefficient (SRF), and the geometric state of the bedrock ( RQD/$J_n$), shear strength of joints ($J_r$/ $J_a$), and environmental factors ($J_w$ /SRF) (Barton et al., 1974). Although there are differences in the factors between RMR and Q-System, the strength characteristics of the intact rock and the characteristics of the discontinuity surface are considered important.

However, there are technical and economic difficulties in evaluating the stress and rock conditions acting on the local bedrock. Moreover, uncertainties associated with the engineered geological properties of rocks can add complexity to the problem. As a result, the factors in current methods contain various uncertainties, along with human limitations induced by the evaluator's subjective judgment. In addition, the current methods cannot offer immediate use of the testing results due to technology limitations, experience, and time constrains.

In this study, we estimate the UCS from rock images using a Deep Learning algorithm. Moreover, we compare and analyze various data arrangements to create an optimized model with higher performance. Finally, we discuss the possible extension of this work for rock evaluation at the tunnel scale through Deep Learning.

## 2. MATERIALS AND METHODS

The first model used in this study was ResNet, a model that has the advantage of making it possible to have good performance even in deeper models through residual learning which is achieved by reducing overfitting (He et al., 2016). The architecture of the ResNet model used in this study is shown in Fig. 1. Pooling is used to reduce overfitting by lowering the resolution, and Batch Normalization as well as Relu Activation to eliminate negative trends in the subsequent model modifications. During training, rock images along with their corresponding UCS are used as input parameters. The images are from laboratory samples for UCS testing. After training, when an image is provided, the model can predict its UCS value.

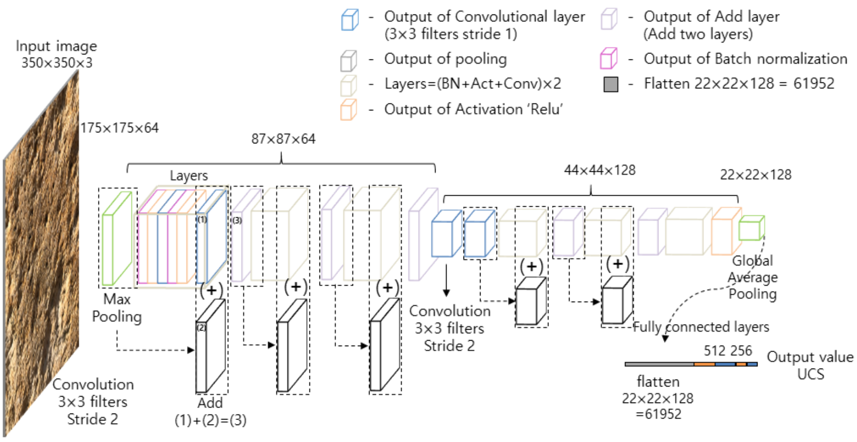


Fig. 1 ResNet architecture used in this study to predict UCS based on rock images.

The second model implemented in this study was Inception, and upgraded model from ImageNet. This model improves the performance by first reducing the channels, extracting first extracting the features of the data with 4 convolutions and performing a 1×1 convolution operation (Szegedy et al., 2015).

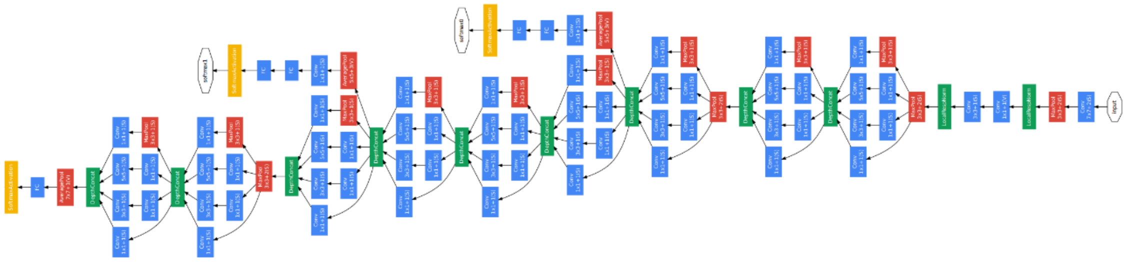

Fig. 2 Inception architecture (after Szegedy et al., 2015).

Moreover, in this study the brightness of the image was determined as an important factor as it affects the prediction results. Then, the Gray Mean Value (GMV), which is the average of the gray values the pixel in each image was quantified and used during training. Fig. 3 shows how images with the same UCS value, images can have different GMV based on the photo condition. In one data arrangement of this study, the images were increased to six GMV groups to reduce the image brightness influence during training, and the error when using similar images but with different brightness level.

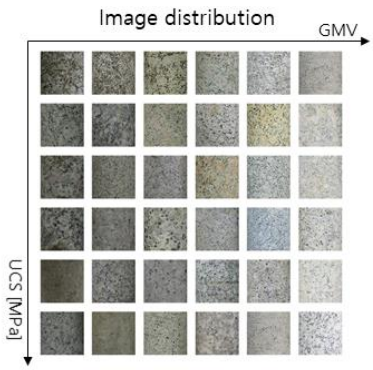


Fig. 3 Gray Mean Value (GMV) and Uniaxial Compressive Strength (UCS).

In this study, six data arrangements are compared, with the first five predicted using ResNet and the last using Inception; (i) using one rock type only (granite), (ii) increasing GMV divided into 6 ranges, (iii) using data augmentation, (iv) optimal batch size, (v) Ensemble technique, and (vi) Inception model.

## 3. RESULTS

For this model we fixed the number of Epochs to 250, and implemented the activation functions Selu, Relu, Linearn and Adam Optimizer. The prediction results are reported as comparisons of the predicted UCS values (in MPa), and the measured UCS for the two models under different data arrangements (Fig. 4). Also, equations of fitted lines to the data and their proportion of variance ($R^2$) are provided. The last case (Fig. 4f) shows the implementation of the Inception model which returned the highest correlation coefficient (0.82). Then, although the implemented methods are not free from errors, it is considered that they can serve to provide faster on-hand tools to make objective and reliable judgements when evaluating bedrock.

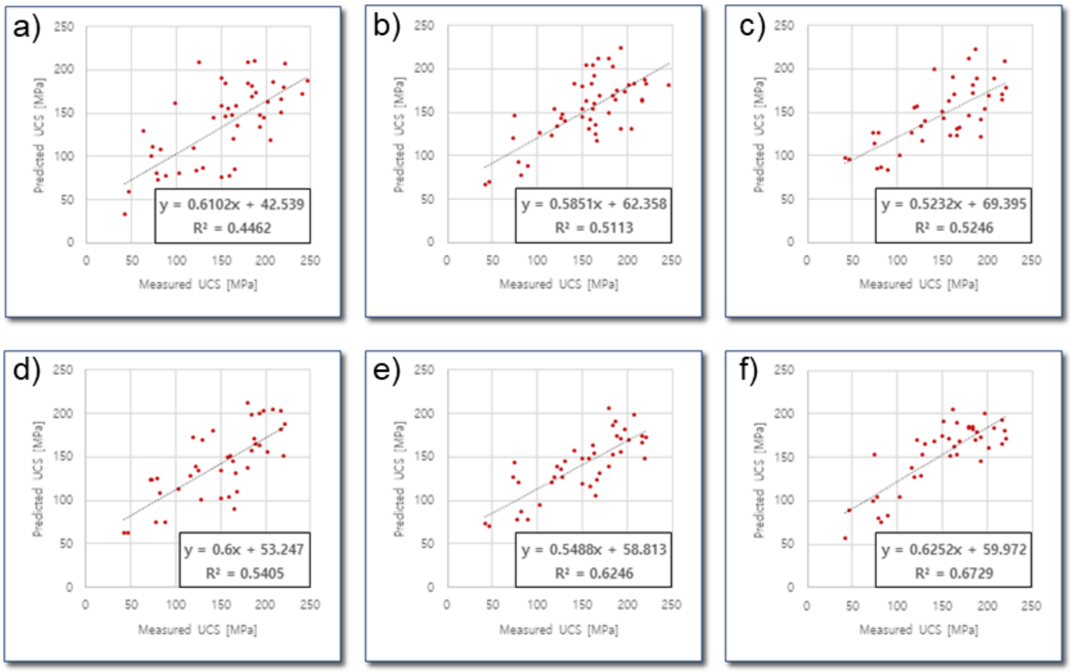


Fig. 4 UCS predictions from different methods; (a) using one rock type only (granite), (b) increasing GMV divided into 6 ranges, (c) using data augmentation, (d) optimal batch size, (e) Ensemble technique, (f) Inception model.

## 4. CONCLUSIONS

In this study, digital-image-based rock uniaxial compressive strength prediction was assessed. Two Deep Learning models were compared, ResNet and Inception. The results showed a better performance of the Inception model, with a correlation coefficient of 0.82, making this method worth of consideration for field applications.

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