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Estimation of Cerchar Abrasivity Index using machine learning based regression

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ABSTRACT

The most widely used parameter to represent rock abrasiveness is the Cerchar Abrasivity Index (CAI). The CAI value can be applied to wear predictions for TBM cutters. Many researchers showed that the CAI was strongly influenced by the degree of cementation, strength and amount of abrasive minerals, i.e. quartz content or equivalent quartz content in the rocks. The relationship between properties of rocks and CAI was explored in this research. A database with 223 observations was constructed, including rock types, uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), equivalent quartz content (EQC), quartz content, brittleness indices, and CAI. A linear model was developed by selecting independent variables while taking into consideration multicollinearity after running multiple linear regression analyses. Machine learning-based regression methods including support vector regression (SVR), regression tree (RT) regression, and k-nearest neighbors (KNN) regression were used in addition to multiple linear regression. The results of the KNN model predicts the best performance.

1. INTRODUCTION

The most widely used parameter to represent rock abrasiveness is the Cerchar Abrasivity Index (CAI). Cerchar abrasivity test is a fast and cost-effective method for evaluating abrasiveness of rocks (Ko et al. 2016). The CAI value can be applied to wear predictions for disc cutters in TBM tunneling. CSM model (Rostami 1997) estimated disc cutter life from CAI. The CAI and weight loss of disc cutters were employed by Gehring (1995). Frenzel (2011) examined the correlation between CAI and radial abrasion of 17-inch disc cutters.

CAI has been the subject of numerous studies. The influence of geomechanical parameters such as density, porosity, elastic modulus, rock brittleness and strength, as

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well as petrographic factors such as quartz content and equivalent quartz content, on CAI were primarily investigated. Many researchers showed that the CAI was strongly influenced by the degree of cementation, strength and amount of abrasive minerals, i.e. quartz content or equivalent quartz content in the rocks (Al-Ameen and Waller 1994, Plinninger et al. 2003, Rostami et al. 2014, Moradizadeh et al. 2016, Ko et al. 2016, Yaralı 2017, Ozdogan et al. 2018, Kahraman et al. 2018, Erarslan 2019).

This research investigated the relationship between rock properties and CAI. In particular, the properties of the rocks used in this study are strength, brittleness, and quartz content or equivalent quartz content, which can be measured relatively easily. An extensive database containing information on rock types, uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), equivalent quartz content (EQC), quartz content, brittleness indexes, and CAI has been developed. The information was gathered from published articles and the Geotechnical Data Report (GDR) of various tunneling projects. The followings are the brittleness indexes used in this study, which are a function of compressive and tensile strength of rocks (Meng et al. 2021).

$$B_1 = \frac{\sigma_c}{\sigma_t} \tag{1}$$

$$B_2 = \frac{\sigma_c - \sigma_t}{\sigma_c + \sigma_t} \tag{2}$$

$$B_3 = \frac{\sigma_c + \sigma_t}{2} \tag{3}$$

$$B_4 = \frac{\sigma_c \sigma_t}{2} \tag{4}$$

$$B_5 = \sqrt{\frac{\sigma_c \sigma_t}{2}} \tag{5}$$

Where, σ_c is uniaxial compressive strength and σ_t is Brazilian tensile strength.

After performing multiple linear regression analyses, a linear model was developed by selecting independent variables while taking into account multicollinearity. Machine learning-based regression methods including support vector regression (SVR), regression tree regression (RFR), and k-nearest neighbors (KNN) regression were used in addition to multiple linear regression.

2. MULTIPLE LINEAR REGRESSION ANALYSES

The dataset includes CAI, rock types, strength-related UCS and BTS, petrographic factors quartz and equivalent quartz content, and brittleness indexes B1 to B5. In addition, the new brittleness index, Bi, which is a function of UCS and BTS, and has been proposed from nonlinear regression with CAI. The data includes 223 observations.

$$B_i = \sigma_c^{1/12} \cdot \sigma_t^{1/3} \tag{6}$$

The histogram of variables is presented in Fig. 1. CAI is a dependent feature, and the rest are independent features. The data was divided into two groups: training and test set. The training set consisted of 80% of the data, whereas the test set consisted of the remaining 20%.

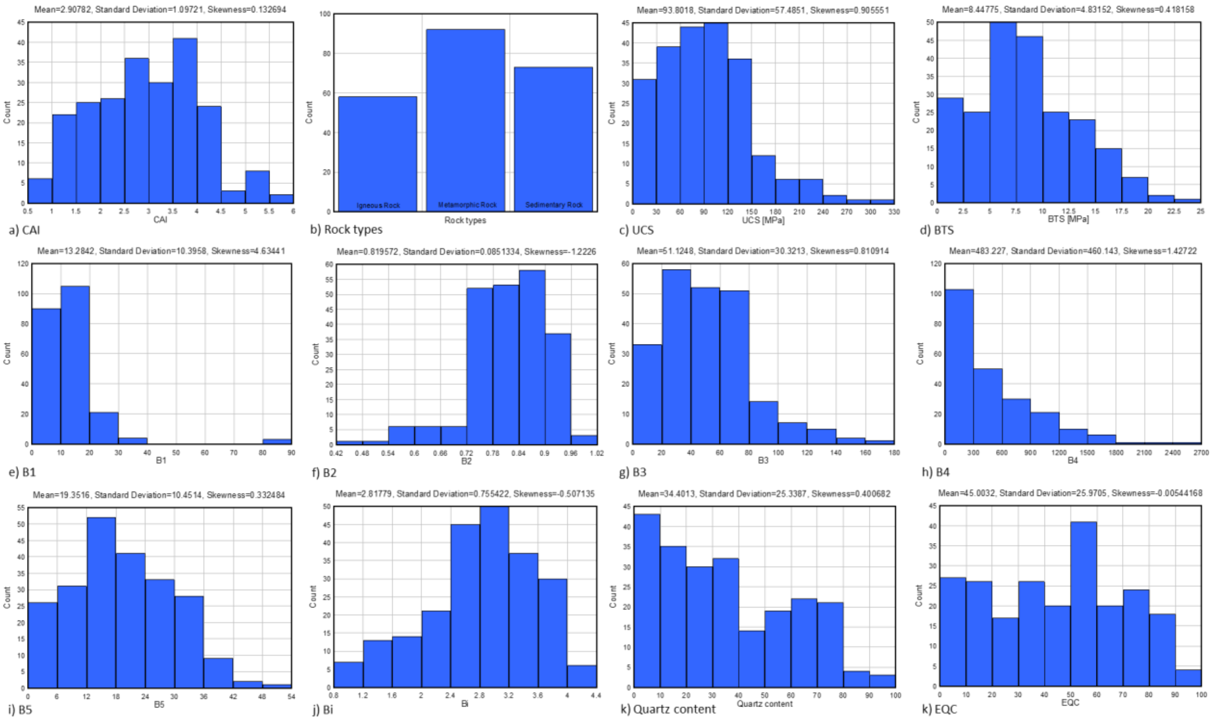

Fig. 1 Histogram of variables

Brittleness indices B1 through Bi were derived using UCS and BTS, the multicollinearity of independent features should be evaluated. Multicollinearity can be detected via variable inflation factor (VIF). VIF score of an independent variable represents how well the variable is explained by other independent variables. In general, VIF exceeding 10 indicates high multicollinearity between the independent variable and the others. Table 1 shows the VIFs for each independent variables.

Table 1 VIFs for each independent variables

	Rock type	UCS	BTS	B1	B2	B4	B5	Bi	Quartz content	EQC
VIF	1.82	140.48	180.67	3.59	13.70	97.97	1151.41	180.38	13.04	12.38

Stepwise regression was performed to select the explanatory variables to be used in the multiple regression model. Stepwise regression selected independent variable of

Rock type, UCS, B2, Bi and quartz content and gave the coefficient of determination (R^2) of 0.787. The best prediction model of the multiple regression is expressed as:

$$CAI = 0.017QC - 0.016UCS + 1.839B_i + 6.929B_2 - 0.836RT - 5.342 \quad (7)$$

where, QC is quartz content and RT is rock type, 1 for igneous, 2 for metamorphic, and 3 for sedimentary rocks.

Fig. 2 shows the regression plot for the training and test data of the multiple linear regression model. The VIFs for the selected independent variables are shown in Table 2.

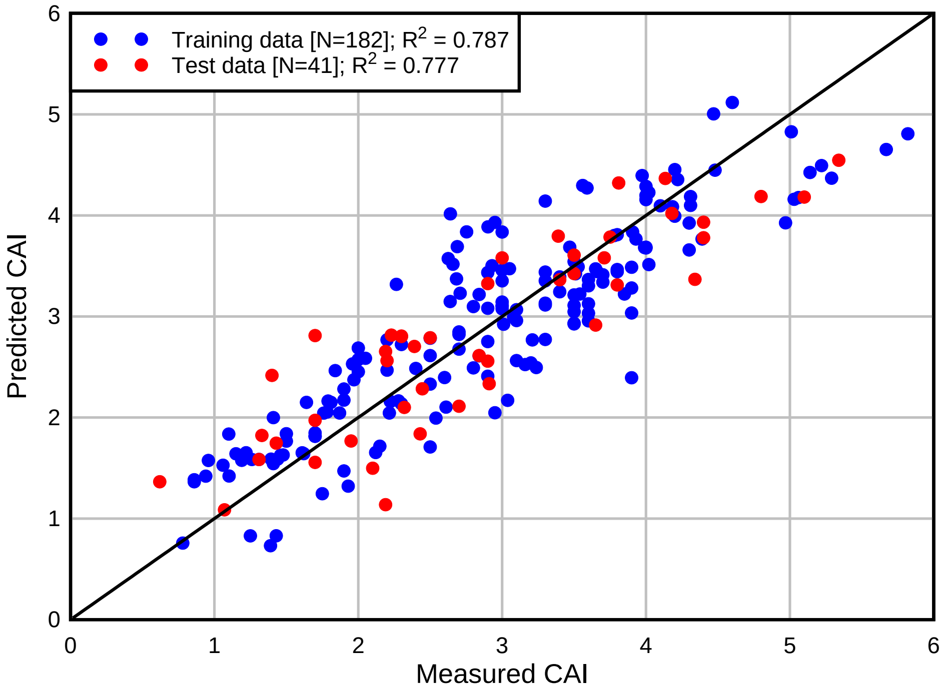

Fig. 2 Multiple linear regression plot for the training and test data

Table 2 VIFs for the selected independent variables

	Rock type	UCS	B2	Bi	Quartz content
VIF	1.233	7.837	3.469	7.197	1.102

3. MACHINE LEARNING-BASED REGRESSION ANALYSES

In this study, 3 different machine learning-based regression methods were employed for predicting CAI. The methods included support vector regression (SVR), regression tree (RT) regression, and k-nearest neighbors (KNN) regression. Rock type, UCS, B2, Bi and quartz content were used as independent variables. Three evaluation criteria, mean squared error (MSE), mean absolute percentage error (MAPE) and coefficient of determination (r^2) assessed performance of the developed models.

Table 3 provides the training and test results of the applied models including the multiple linear regression model. The result indicates that the best model is the k-nearest neighbors (KNN) regression model for the training phase. In contrast, the multiple linear regression (MLR) model yields the worst results for the training phase. Support vector regression (SVR) model gives the best results for the test phase and regression tree (RT) regression model produces the worst results for the test phase. Overall, the results of the KNN model predicts the best performance when both training and test phase are taken into account. Fig. 3 depicts the KNN model's regression plot for both the training and test sets of data.

Table 3 Training and test results of the applied models

Methods	Training			Test		
	MSE	MAPE	r^2	MSE	MAPE	r^2
MLR	0.25	16.4	0.787	0.28	19.77	0.777
SVR	0.15	11.21	0.879	0.25	17.48	0.808
RTR	0.24	15.34	0.800	0.55	25.94	0.571
KNN	0.09	9.57	0.919	0.28	17.82	0.782

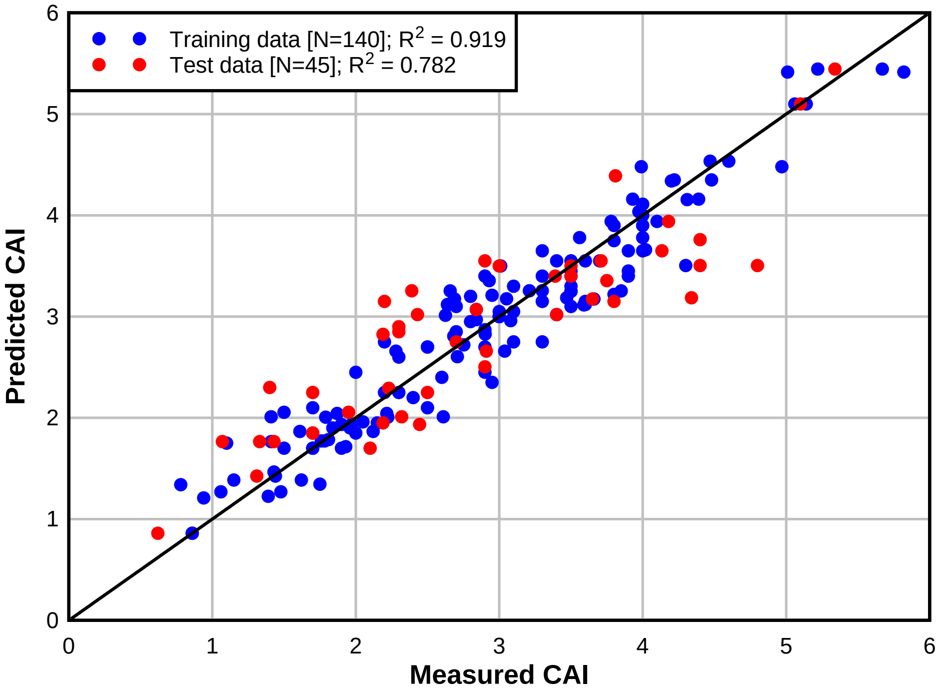

Fig. 3 KNN regression plot for the training and test data

4. CONCLUSIONS

The purpose of this study was to examine the relationship between rock properties and CAI. The properties of the rocks used in this study are strength, brittleness, and quartz content or equivalent quartz content, all of which can be obtained relatively easily. A database with 223 observations was constructed, including rock types, uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), equivalent quartz content (EQC), quartz content, brittleness indices, and CAI. A linear model was developed by selecting independent variables while taking into consideration multicollinearity after running multiple linear regression analyses. Machine learning-based regression methods including support vector regression (SVR), regression tree regression (RFR), and k-nearest neighbors (KNN) regression were used in addition to multiple linear regression. The results of the KNN model predicts the best performance.

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