



ORIGINAL PAPER

PREDICTION OF UNIAXIAL COMPRESSIVE STRENGTH OF ROCKS BY NON-DESTRUCTIVE TESTING VIA DIFFERENT MACHINE LEARNING ALGORITHMS

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ARTICLE INFO

Article history:

Received 15 May 2025

Accepted 26 June 2025

Available online 3 July 2025

Keywords:

Uniaxial compressive strength prediction

Schmidt rebound hammer

Leeb hardness

Random Forest

Rock strength

ABSTRACT

Uniaxial Compressive Strength (UCS) is a fundamental parameter in engineering projects, often serving as a primary input for various analyses. The direct determination of UCS requires laboratory sample preparation in accordance with established standards. However, in cases where sample extraction is unfeasible due to the rock type or field conditions, UCS must be estimated through indirect methods. Over the years, numerous rock properties such as porosity, density, P- wave velocity, and Schmidt hammer rebound value have been employed as predictor variables for UCS estimation. In this study, UCS was predicted using Schmidt hammer rebound (SHR) and Leeb hardness (HL), which are practical, cost-effective, and non-destructive testing methods. Various machine learning algorithms including Linear Regression, Ridge Regression, Lasso Regression, ElasticNet Regression, Random Forest, Gradient Boosting, and Support Vector Regression were applied for prediction. The correlation coefficient (R^2) obtained from these models ranged between 0.75 and 1.00. Among the tested models, the Random Forest (RF) algorithm demonstrated the highest prediction accuracy, with validation metrics of RMSE = 1.93, MSE = 0.87, and R^2 .

1. INTRODUCTION

The UCS of rocks is defined as the strength of rock materials separated by discontinuities. To determine the behavior of intact rocks, the UCS test is conducted in the laboratory. UCS is primarily applied in accordance with the standards recommended by the American Society for Testing and Materials (ASTM) or the International Society for Rock Mechanics (ISRM) (ISRM, 2007; ASTM, 2014). UCS serves as a key parameter in various rock engineering projects, such as tunnel construction, excavation, drilling, and slope stability. Although this test is time-consuming, costly, and destructive, its success in preparing samples depends on the physical properties of the rock. Due to these disadvantages in the implementation of the UCS test, it is scientifically crucial to develop economical, practical, non-destructive, and reliable methods for predicting the UCS of rocks in order to meet the needs of engineering applications and research.

Some researchers have attempted to predict UCS using simple regression models based on rock properties. Parameters such as SHR, P-wave velocity (V_p), and point load strength (PLS) are commonly used for this purpose (Kahraman, 2001; Yılmaz and Sendir, 2002; Çobanoğlu and Çelik, 2008; Khandelwal and Singh, 2009; Kahraman, 2014; Mohamad et al., 2015). However, empirical relationships between UCS and a single independent

variable may not provide reliable predictions in rock engineering applications (Dehghan et al., 2010; Beiki et al., 2013). To address these limitations, multiple regression (MR) analyses considering multiple rock properties have been developed. However, the assumption of linear dependence in the multiple regression method is constrained by the fact that the relationship between UCS and independent variables may not always be linear. UCS can exhibit polynomial, exponential, or logarithmic relationships with certain rock properties. Furthermore, an MR model with numerous independent variables may demonstrate high fit to training data but exhibit poor generalization performance on new test data. Additionally, high correlation among independent variables (multicollinearity) can lead to meaningless regression coefficients. For these reasons, machine learning and artificial intelligence techniques are increasingly preferred in UCS prediction. These methods have the potential to capture non-linear relationships more effectively, thereby improving prediction accuracy. In recent years, there has been a significant increase in studies aimed at predicting UCS using machine learning algorithms and artificial intelligence models, incorporating rock properties such as physical, mechanical, and mineralogical characteristics as parameters (Table 1). As seen in Table 1, several researchers have developed UCS models using different input parameters and methods

Table 1 Several machine learning techniques from literature have been utilized to predict UCS.

Rock Type	Number of Dataset	Inputs	Models	Validation metric results	References
Travertine	30	$I_{s(50)}$, n , V_p and SHR	ANN	R^2 :0.86	Denghan et al. (2010)
Marl limestone, Dolomite, Calcite	72	n , p and V_p	GEP	r : 0.77; RMSE: 16.4	Beiki et al. (2013)
Different rocks	15	V_p , p and V_s	ANFIS	R^2 :0.86; MAPE: 9.6; RMSE: 5.2; VAF: 92.65	Singh et al. [11]
Carbonate racks	55	Mineralog, G_s , n , I_d , n_e , V_k and V_p	ELM SVM GRNN	R^2 : 0.7920; MAPE:14.67 R^2 : 0.7987; MAPE:12.46 R^2 : 0.7669; MAPE:12.61	Liu et al. (2013)
Carbonate rocks	163	p , n , V_p , v and PLS	MR ANN	R^2 :0.91; RMSE: 11.4 R^2 :0.97; RMSE: 6.6	Madhubabu et al. (2016)
Travertine	85	V_p , SHR and p	SVM ANFIS MLP SFL MFL	R^2 : 0.95; RMSE: 2.14; MAE:1.35 R^2 : 0.91; RMSE: 2.68; MAE:1.63 R^2 : 0.84; RMSE: 3.51; MAE:2.28 R^2 : 0.85; RMSE: 3.51; MAE:2.59 R^2 : 0.76; RMSE: 4.38; MAE:2.78	Barzegar et al. (2016)
Limestone, porous limestone, limestone marl	482	V_d and E_d	ANN SVR SR	R^2 :0.9040; RMSE:2.0 R^2 :0.9220; RMSE:1.31 R^2 :0.8970; RMSE:2.74	Aboutaleb et al. (2018)
Sandstone and Limestone	45	n , p and V_p	ANFIS	R^2 :0.9350; RMSE:4.69; MAPE: 16.53; VAF:95.60	Umrao et al. (2018)
Limestone, Marble, dolomite	90	SHR, V_p , L and V_k	LS-SVM MR	R^2 : 0.87; RMSE: 16.61; E:0.79 R^2 : 0.78; RMSE: 18.56; E:0.74	Çelik (2019)
Limestone	115	p , V_p , n and v	LLNF ANN COA-ANN	R^2 :0.98; NMSE: 2.54; VAF: 80.24 R^2 :0.80; NMSE: 5.20; VAF: 73.00 R^2 :0.96; NMSE: 3.06; VAF: 75.18	Mokhtari and Behnia (2019)
Basalt	56	V_k , V_p , I_d , SHR, $I_{s(50)}$, and BTS	ANN1 ANN2	R^2 :0.99; RMSE:1.54 R^2 :0.94; RMSE:1.73	Barham et al. (2020)
Basalt, limestone, dolostone	30	SH, V_p and BTS	M5MT MLPNN ELM	R^2 :0.96; RMSE: 4.08; MAE: 3.22; VAF: 96.63 R^2 :0.99; RMSE: 1.34; MAE: 0.79; VAF: 99.74 R^2 :0.98; RMSE: 2.34; MAE: 1.98; VAF: 98.82	Gül et al. (2021)
Claystone, Granite, Schist and Sandstone, Travertine,	170	SHR, n , V_p , and $I_{s(50)}$	LSTM DNN	R^2 : 0.93; MAE:0.21; RMSE: 2.84; MSE: 8.05 R^2 : 0.90; MAE:0.24; RMSE: 3.22; MSE: 10.37	Mahmoodzadeh et al. (2021)

Limestone, Slate, Dolomite and Marl			KNN GPR SVR DT	R2: 0.79; MAE:0.15; RMSE: 2.06; MSE: 4.25 R2: 0.99; MAE:0.04; RMSE: 0.52; MSE: 0.27 R2: 0.93; MAE:0.08; RMSE: 1.09; MSE: 1.20 R2: 0.94; MAE:0.05; RMSE: 0.005; MSE: 0.70	
Carbonate formation	1935	WOB, T _{rq} , SPP, RPM, FLR, ROP	ANN	R: 0.97; AAPE: 0.65	Hiba et al. (2022)
Granite, Sandstone, Metamorphic	60	I _{s(50)} , BPI, SRH, G _s and n	ANN RF MLR	R2: 0.92; MAE: 9.79 R2: 0.94; MAE: 8.68 R2: 0.89; MAE: 13.79	Dadhich et al. (2022)
Sedimentary rocks	45	p, n, V _p , PLS, BTS, BPI	MR ANN ANFIS	r: 0.82; RMSE: 7.43 r: 0.96; RMSE: 3.74 r: 0.99; RMSE: 0.5	Khajevand (2023)
Different rocks	344	SHR, I _{s(50)} , PLS and n	XGBoost AOA- XGBoost	R2:0.84; RMSE: 19.22; MAE: 12.95; MAPE: 19.29 R2:0.91; RMSE: 14.69; MAE: 11.70; MAPE: 18.15	Sun et al. (2024)
Samples were compiled from the literature	200	CP, MDD, OMC, GGBS, PL, LL, PI	LR	R ² :0.57; RMSE: 0.65; MAE: 0.47; MSE: 0.43	Mohammed et al. (2025)
			DT	R ² :0.92; RMSE: 0.09; MAE: 0.06; MSE: 0.08	
			RF	R ² :0.93; RMSE: 0.08; MAE: 0.06; MSE: 0.00	
			ANN	R ² :0.94; RMSE: 0.15; MAE: 0.08; MSE: 0.02	
			GB XGB	R ² :0.93; RMSE: 0.08; MAE: 0.05; MSE: 0.00 R ² :0.95; RMSE: 0.07; MAE: 0.04; MSE: 0.00	
Magmatic rocks	95	HL, SHR	MLR ANN	R ² :0.78 R ² :0.84	İnce et al. (2025)
Carbonate Rocks	110	I _{s(50)} , BTS	MLR ANN	R ² :0.78; RMSE: 0.34 R ² :0.84; RMSE: 0.26	Setayeshirad et al. (2025)
Different rocks	199	V _p , p, C, AIF	CNN GRU LSTM RNN	R ² :0.993; RMSE: 4.79; MAPE: 2.1 R ² :0.992; RMSE: 5.05; MAPE: 2.8 R ² :0.998; RMSE: 2.82; MAPE: 2.1 R ² :0.990; RMSE: 5.69; MAPE: 3.6	Ding et al. (2025)

Note:

Inputs=AIF: Angle of internal friction; **BPI**: Block punch index; **BTS**: Brazilian tensile strength; **C**: Cohesion; **CP**: Curing period; **Ed**: Dynamic Young's modulus; **GGBS**: Ground granulated blast furnace slag; **Gs**: Specific gravity; **HL**: Leeb hardness; **Ia**: Slake durability; **I_{s(50)}**:Point load strength; **L**: Cubic sample size; **LL**: Liquid limit; **MDD**: Maximum dry density; **n**: Porosity; **n_e**: Effective porosity; **OMC**: Optimum moisture content; **p**: density; **PI**: Plasticity index; **PL**: Plastic limit; **PLS**: Point load strength; **ROP**: Rate of penetration; **SH**: Shore hardness; **SHR**: Schmidt rebound hammer; **SPP**: Standpipe pressure; **T**: torque; **Q**: Drilling injection rate; **V_p**: P-wave velocity; **V_s**: S-wave velocity; **WOB**: Weight on bit; **Y_k**: Dry unit weight; **v**: Poisson's ratio;

Models=ANFIS: Adaptive neuro-fuzzy inference system; **ANN**: Artificial neural network; **AOA**: Archimedes optimization algorithm; **CNN**: Convolutional Neural Networks; **COA-ANN**: cuckoo optimization algorithm-artificial neural network; **DNN**: Deep neural networks; **DT**: Decision tree; **ELM**: Extreme learning machine; **GEP**: Gene expression programming; **GPR**: Gaussian process regression; **GRNN**: Generalized regression neural network; **GRU**: Gated Recurrent Units; **KNN**: K-nearest neighbor; **LLNF**: Local linear neuro-fuzzy; **LSTM**: Long short term memory; **MFL**: Mamdani fuzzy logic; **MLP**: Multilayer perceptron; **MLPNN**: Multilayer perceptron neural network ;**MLR** Multivariate linear regression; **MR**: Multiple regression analysis; **M5MT**: M5 Model Tree; **RF**: Random forest; **RNN**: Recurrent Neural Networks; **SFL**: Sugeno fuzzy logic; **SR**: Simple regression analysis; **SVR**: Support vector regression; **XGBoost**: extreme gradient boosting

Validation metric results= **AAPE**: Average absolute percentage error; **E**: Skill score; **MAE**: Mean absolute error; **MAPE**: Mean absolute percentage error; **MSE**: Mean squared error; **NMSE**: Normalized mean squared error; **r**: correlation; **R²**: Coefficient of determination; **RMSE**: Root of mean square error; **VAF**: Variance account for

Table 2 The location and type of rock samples.

Sample	Location	Rock type	Sample	Location	Rock type
1	Karayazı/Nevşehir	Pyroclastic	30	Kayseri-11	Pyroclastic
2	Sadıklar/Konya	Pyroclastic	31	Kayseri-12	Volcanic
3	Sille/Konya-1	Volcanic	32	Afyonkarahisar-1	Pyroclastic
4	Selime/Aksaray	Pyroclastic	33	Afyonkarahisar-2	Volcanic
5	Demirci/Aksaray	Pyroclastic	34	Denizli	Volcanic
6	Gümüşler/Niğde	Metamorphic	35	Ardıçlı/Konya-1	Pyroclastic
7	Niğde-1	Pyroclastic	36	Midyat/Mardin	Sedimentary
8	Niğde-2	Pyroclastic	37	Sille/Konya-3	Volcanic
9	Kayseri-1	Pyroclastic	38	Gürşehir/Aksaray	Pyroclastic
10	Kayseri-2	Pyroclastic	39	Mut/Mersin	Sedimentary
11	Kayseri-3	Pyroclastic	40	Afyonkarahisar-3	Volcanic
12	Kayseri-4	Pyroclastic	41	Kızılören/Konya	Pyroclastic
13	Kayseri-5	Pyroclastic	42	Ankara-2	Volcanic
14	Kayseri-6	Pyroclastic	43	Ankara-3	Volcanic
14	Kayseri-7	Pyroclastic	44	Aksaray-2	Plutonic
15	Kayseri-8	Pyroclastic	45	Kayseri-13	Pyroclastic
16	Kayseri-9	Pyroclastic	46	Nevşehir	Pyroclastic
17	Aksaray-1	Plutonic	47	Sille/Konya-4	Pyroclastic
18	Yaylak/Aksaray	Plutonic	48	Kayseri-14	Pyroclastic
19	Ortaköy/Aksaray	Plutonic	49	Muğla	Metamorphic
20	Giresun	Plutonic	50	Aksaray-3	Plutonic
21	Yunt/Manisa	Volcanic	51	Karaman-2	Sedimentary
22	Kayseri-10	Pyroclastic	52	Karaman-3	Sedimentary
23	Çanakkale	Plutonic	53	Özkonak/Nevşehir	Pyroclastic
24	Giresun	Plutonic	54	Kayseri-15	Pyroclastic
25	Ankara-1	Volcanic	55	İscehisar/Afyonkarahisar	Volcanic
26	Kulu/Konya	Volcanic	56	Niğde-3	Pyroclastic
27	Sille/Konya-2	Pyroclastic	57	Kayseri-16	Volcanic
28	Kilistra/Konya	Pyroclastic	58	Ardıçlı/Konya-2	Pyroclastic
29	Karaman-1	Sedimentary			

(e.g., artificial neural network (ANN), RFR, GEP, ELM, etc.). The correlation coefficients obtained for different rock groups in these models range from 0.57 to 0.99. Numerous researchers have developed models to estimate UCS using surface hardness parameters such as SHR and HL. In these studies, either SHR or HL has been used as an input variable in statistical or ANN-based models to predict UCS values (Çelik and Çobanoğlu, 2019; Bilen, 2021; Sadeghi et al., 2022; Asteris et al., 2024; İnce et al., 2025). In the study by İnce et al. (2025), an ANN model was developed to estimate the UCS of igneous rocks using both SHR and HL as input parameters, achieving a correlation coefficient of 0.84. However, the number of ANN models that utilize surface hardness data to predict the UCS of different rock groups remains quite limited.

In this study, 58 samples collected from different rock groups (igneous, sedimentary, and metamorphic) were used, with SHR and HL values as input parameters derived from non-destructive tests. The UCS values were predicted using various machine learning algorithms, including Linear Regression (LR), Ridge Regression (RR), Lasso Regression (LsR), ElasticNet Regression (ENR), Random Forest

2. MATERIALS AND METHODS

As part of field studies, a total of 58 rock samples were collected from various quarries located in different regions of Anatolia, including 31 pyroclastic, 13 volcanic, 8 plutonic, 4 sedimentary, and 2 metamorphic types. The locations and rock types of these samples are presented in Table 2.

From each quarry, a block sample approximately 25 cm x 30 cm x 20 cm in size was collected (Fig. 1a). Five cubic samples with an edge length of 7 cm were prepared from each block sample, following the methods recommended in TS EN-1936 (2010) (Fig. 1b). SHR tests were conducted on the block samples, while HL and UCS tests were performed on the prepared cubic specimens (Fig. 2).

The SHR test was conducted in accordance with the standards recommended in ASTM D5873, (2014) using an L-type hammer (Fig. 3a). To avoid directional bias in the hammer, it was held horizontally and perpendicular to the measurement surface. Ten measurements were taken from different areas of each rock sample to determine the average SHR value. Measurements deviating more than seven units from the mean were excluded, and the SHR value was calculated by averaging the remaining values. This

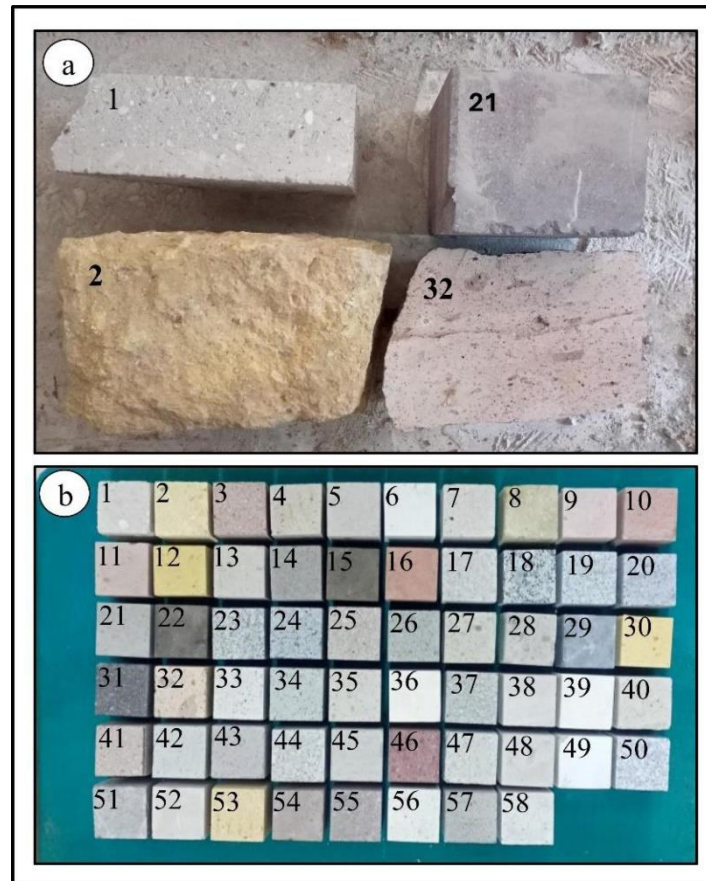


Fig. 1 Some rock block samples (a), cubic samples of different rock types (b).

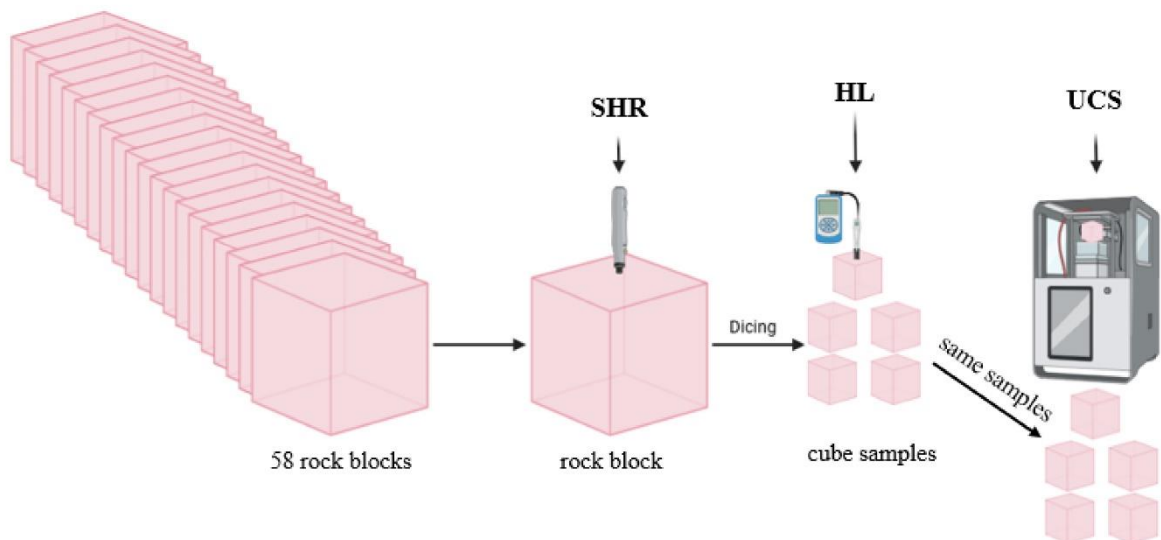


Fig. 2 Experimental stages conducted on rock blocks.

process was repeated five times for each 20cmx30cmx30cm rock sample, resulting in five separate SHR values for each rock specimen.

Since there is no standard for the HL test on rocks, the HL measurements were determined following the methods proposed by İnce and Bozdağ (2024). The HL value measurements were conducted using the Insize ISH-PHB testing device with

a D-probe (Fig. 3b). The technical specifications of the device include a measurement range of 0 to 999 HL, impact energy of 11 Nmm, and accuracy of ± 6 HL. Prior to determining the HL value, the device was calibrated, and 20 different impact points were selected on the surface of a cubic sample, evenly distributed. The arithmetic mean of these values was then used as the HL value for the sample.

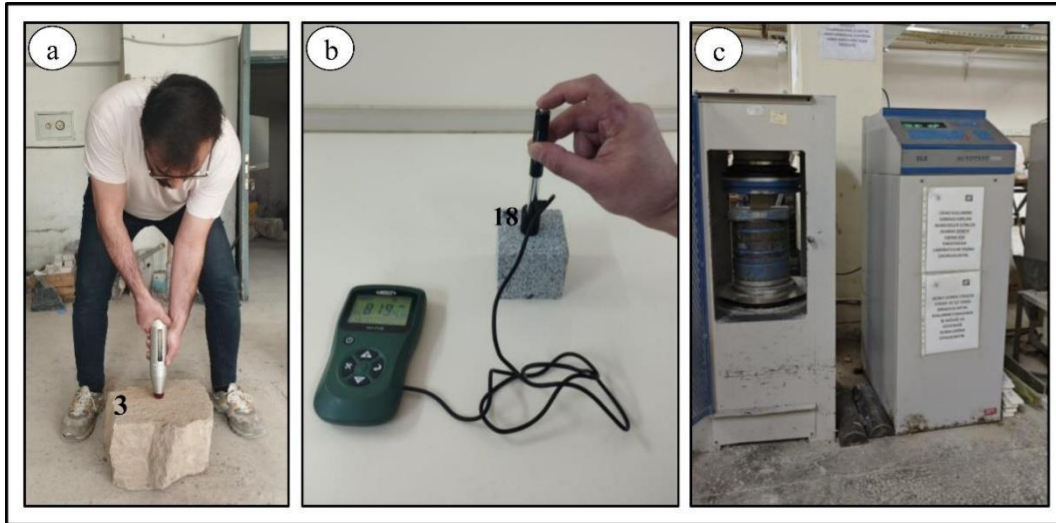


Fig. 3 SHR test (a), HL test (b), UCS test (c).

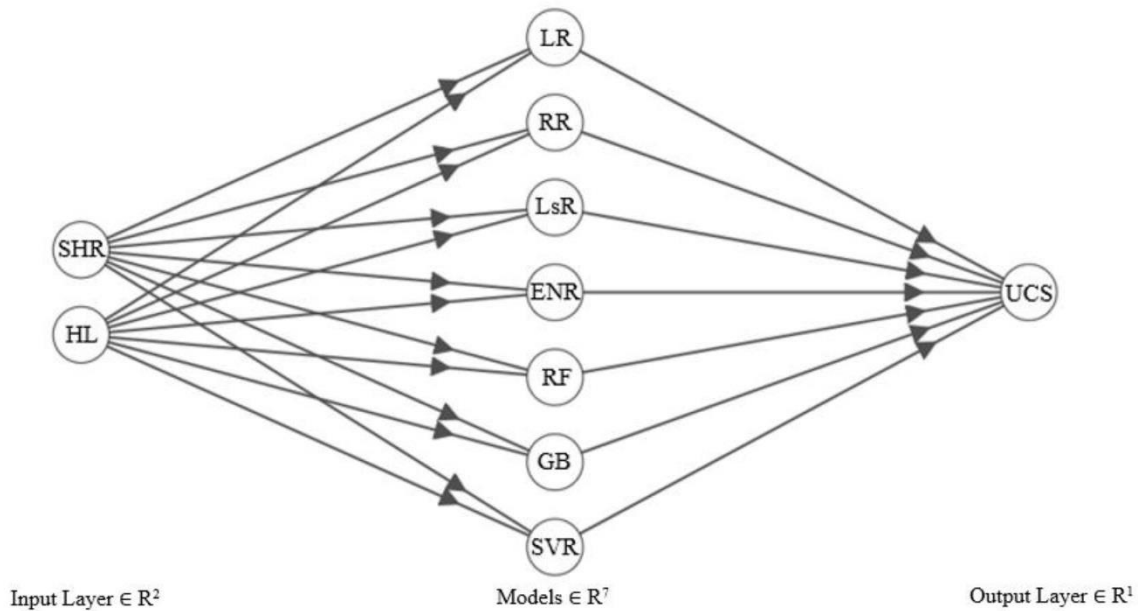


Fig. 4 The general schema for UCS prediction using machine learning algorithm models.

The UCS tests were performed on cubic samples with an edge length of 70 mm, following the methods outlined in TS EN-1926 (2007). An ELE Autotest 3000 test machine with a 3000 kN loading capacity was used for this test (Fig. 3c). The loading rate during the UCS test was set at 1.0 ± 0.5 MPa/s. UCS testing was conducted five times for each rock sample, resulting in five separate UCS values for each sample.

A total of 58 rock samples were tested, with five distinct SHR, HL, and UCS values obtained from each sample, resulting in a total of 290 data points. Consequently, seven different machine learning algorithms Linear Regression (LR), Ridge Regression (RR), Lasso Regression, ElasticNet Regression (ENR), Random Forest (RF), Gradient Boosting (GB), and Support Vector Regression (SVR) were employed in this study to predict the uniaxial compressive strength (UCS, MPa) of rock materials. Table 3

provides a list of the models used in this study, along with their descriptions and mathematical formulas. In the modeling process, SHR and HL were selected as independent variables (input variables), while UCS was considered as the dependent variable (target variable). The general schema for UCS (MPa) prediction using machine learning algorithm models is shown in Figure 4.

The analyses were conducted using the Python programming language, with various regression algorithms applied through the Scikit-learn (Lee, 2019) library. To assess the accuracy of the model, the dataset was divided into training and testing sets. The rock samples in these sets were selected randomly, with 80 % (232 samples) of the total used for the training set and the remaining 20 % (58 samples) allocated for the testing set. While the training data was employed to construct the model, the test data was

Table 3 The models used in the study.

Model	Description	Mathematical Formula	Source
Linear Regression	A statistical technique that models the linear relationship between the dependent variable and independent variables.	$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n +$	Galton (1886)
Ridge Regression	A method that adds an L2 regularization term to linear regression to reduce multicollinearity.	$\hat{\beta} = \arg \min_{\beta} \left(\sum_{i=1}^m (y_i - X_i \beta)^2 + \lambda \sum_{j=1}^n \beta_j^2 \right)$	Hoerl and Kennard (1970)
Lasso Regression	A regression model that includes an L1 regularization term to reduce model complexity through feature selection.	$\hat{\beta} = \arg \min_{\beta} \left(\sum_{i=1}^m (y_i - X_i \beta)^2 + \lambda \sum_{j=1}^n \beta_j \right)$	Tibshirani (1996)
ElasticNet Regression	A model that combines both Ridge and Lasso regression, including both L1 and L2 regularization.	$\hat{\beta} = \arg \min_{\beta} \left(\sum_{i=1}^m (y_i - X_i \beta)^2 + \lambda_1 \sum_{j=1}^n \beta_j + \lambda_2 \sum_{j=1}^n \beta_j^2 \right)$	Zou and Hastie (2005)
Random Forest	An ensemble learning method that creates multiple decision trees to prevent overfitting and improve prediction accuracy.	$f(x) = \frac{1}{T} \sum_{t=1}^T h_t(x)$	Breiman (2001)
Gradient Boosting	A boosting method where each new model improves the errors of the previous model to reduce residual error.	$f_m(x) = f_{m-1}(x) + \eta \cdot h_m(x)$	Friedman (2001)
Support Vector Regression (SVR)	A method that performs nonlinear regression by mapping data into a high-dimensional space.	$\min_{\beta, \epsilon} \left(\frac{1}{2} \beta^T \beta + C \sum_{i=1}^m \xi_i \right)$	Vapnik (1999)

used to evaluate the model's generalization performance. Furthermore, to prevent overfitting, all models were implemented using the default parameters of the scikit-learn library, and no hyperparameter optimization was performed.

The performance of the models was evaluated using various metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), R-squared (R^2), Cross-Validation MSE, and 10-Fold Cross Validation MSE Scores. Table 4 presents the definitions, formulas, and ideal values of the metrics used for validating the model performance.

3. RESULTS AND DISCUSSION

3.1. PHYSICAL AND MECHANIC PROPERTIES OF ROCKS

Statistical analyses of the SHR, HL, and UCS test results for the rocks used in this study are presented in Table 5. The SHR values of the rocks ranged from 10.00 to 60.00, the HL values ranged from 160.00 to 890.00, and the UCS ranged from 1.56 MPa to 121.52 MPa. Based on the skewness and kurtosis statistical values, the data for the SHR and HL parameters were found to be nearly symmetric, with few outliers and a platykurtic distribution. On the other hand, the data for the UCS parameter exhibited right skewness and approached a normal distribution.

The correlations between the SHR, HL, and UCS test results of the rocks used in this study are presented

in Figure 5. A coefficient of determination (R^2) of 0.75 was found between UCS and SHR, 0.71 between UCS and HL, and 0.87 between SHR and HL. These coefficients of determination indicate that significant relationships exist among the test parameters.

3.2. MACHINE LEARNING MODEL PERFORMANCE ANALYSIS AND RESULTS

In recent years, the importance of estimating the UCS of rocks using rapid and practical input parameters, such as SHR and HL, which are classified as non-destructive testing (NDT) methods, has been increasingly emphasized (Çelik and Çobanoğlu, 2019; İnce et al., 2025; Ulusay et al., 2025). İnce et al. (2025) highlighted the effectiveness of the ANN model they developed to predict UCS values based on SHR and HL measurements. In line with this objective, the predictive performance of various machine learning models has been investigated using surface hardness data obtained from devices that operate with both high-energy (SHR) and low-energy (HL) impact mechanisms. In this study, seven different machine learning models were utilized to predict UCS values, and their performances were evaluated using accuracy metrics. The model performance was determined using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), R-squared (R^2), and 10-Fold Cross Validation MSE Scores (Table 6). Furthermore, to assess the generalization ability of the models, cross-

Table 4 The metrics used for validating the performance of the models.

Metric	Definition	Formula	Ideal values	Source
MAPE (Mean Absolute Percentage Error)	Measures the average percentage error between the actual and predicted values.	$MAPE = \frac{1}{n} \sum_{i=1}^n \left \frac{y_i - \hat{y}_i}{y_i} \right $	0	Hyndman and Koehler (2006)
MSE (Mean Squared Error)	Takes the average of the squared errors. It penalizes larger errors more.	$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$	0	Gauss (1809)
RMSE (Root Mean Squared Error)	Takes the square root of the squared errors, providing results on the same scale as the error unit.	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$	0	Gauss (1809)- Nash and Sutcliffe (1970)
MAE (Mean Absolute Error)	Measures the average absolute difference between predicted and actual values.	$MAE = \frac{1}{n} \sum_{i=1}^n y_i - \hat{y}_i $	0	Willmott and Matsuura (2005)
R ² (R-squared, Coefficient of Determination)	Indicates how much of the variance in the target variable is explained by the model.	$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$	1	Pearson (1901)
Cross-Validation MSE	Divides the dataset into training and test sets and calculates errors at different folds.	$CVMSE = \frac{1}{k} \sum_{i=1}^k MSE_i$	0	Fisher (1935)- Kohavi (1995)
10-Fold Cross-Validation MSE	A model validation technique where the dataset is split into 10 equal parts; in each iteration, one part is used for testing and the rest for training. The final metric is the average of all 10 results.	$MSE_{avg} = \frac{1}{10} \sum_{i=1}^{10} MSE_i$	Low variance across folds; minimal average error	Kohavi (1995)

Table 5 Descriptive statistics of the data used in the analysis.

Variables	Data	Minimum	Maximum	Mean	Std. deviation	Skewness	Kurtosis
SHR	290	10.00	60.00	35.70	14.26	-0.012	-1.03
HL	290	160.00	890.00	545.77	209.03	0.05	-1.17
UCS (MPa)	290	1.56	121.52	39.90	30.85	0.89	0.10

SHR: Schmidt hardness, HL: Leeb hardness, UCS (MPa): uniaxial compressive strength

validation MSE values were calculated. The graphs comparing the actual and predicted UCS (MPa) values for each model are presented in Figure 6-7.

Upon analyzing Table 6, it was observed that the best performance was achieved by the Random Forest (RF) and Gradient Boosting (GB) models. For the RF model, the Mean Squared Error (MSE) value for the training set was found to be 0.37, while for the test set, it was 0.87. The R² value for this model was 1.00 in both the training and test sets, indicating an excellent fit to the data. Similarly, for the GB model, the validation metrics for the test set yielded R² and MSE values of 0.98 and 18.74, respectively. These models (RF and GB) can predict the UCS values of rocks with high accuracy. Upon reviewing the learning curves for RF and GB models, it was observed that the training and test errors stabilized beyond a certain point. To further verify whether these models were overfitting, their performance was cross-validated using MSE. The cross-validation results confirmed that both models possess a high generalization ability. The

cross-validation MSE for Random Forest was 0.22, while for Gradient Boosting, it was 11.33. These values are consistent with the performance of the models on the test set and demonstrate their success in learning the complex relationships within the dataset. Regression-based models, such as Ridge, Lasso, and ElasticNet, exhibited similar performance; however, their accuracy remained lower compared to the tree-based methods. The R² values for these models on the test set were around 0.75, and their error rates (MSE and MAE) were higher compared to those of the Random Forest and Gradient Boosting models. The Support Vector Regression (SVR) model showed the lowest performance, with an R² value of 0.64 on the test set. These results indicate that tree-based algorithms outperform regression-based models and are better at learning the complex relationships present in the dataset. To assess the overall performance of the developed machine learning models, the 10-fold cross-validation MSE scores were examined. Among these models, the RF prediction model achieved an

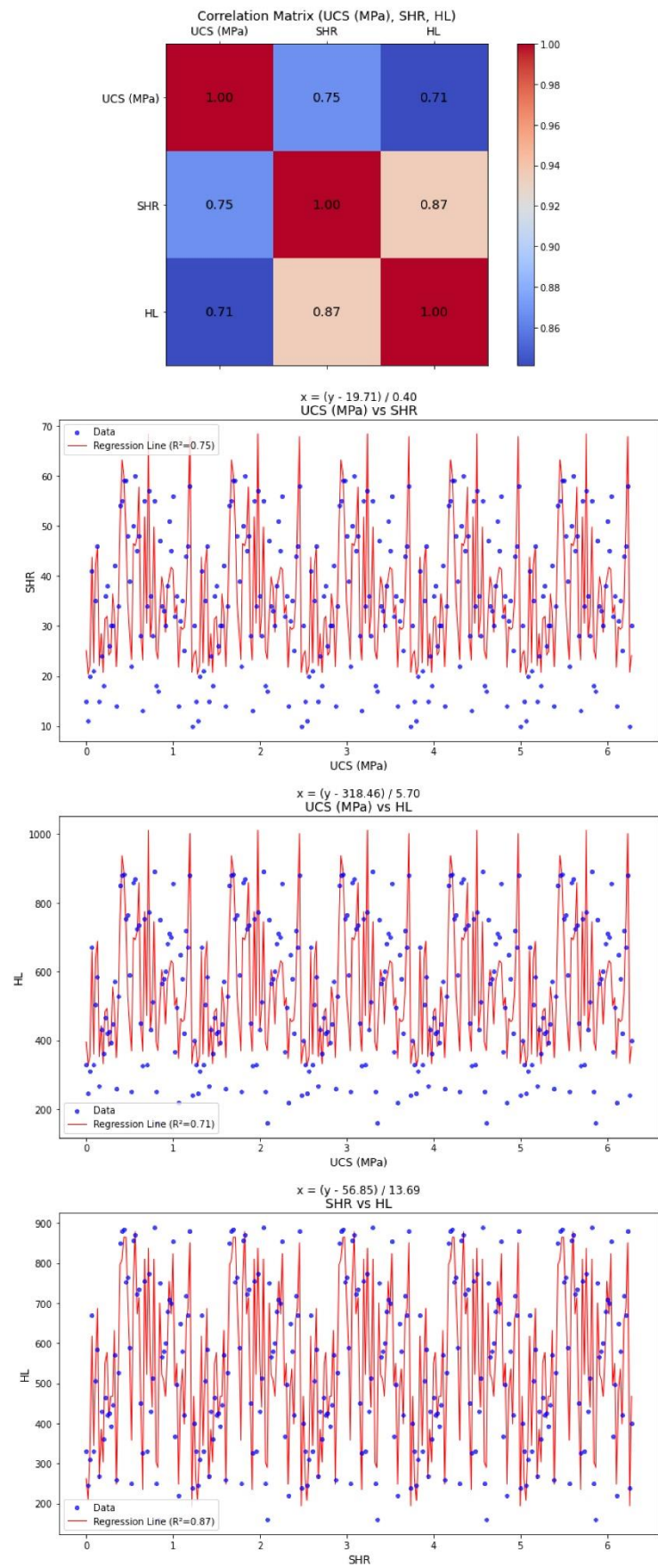


Fig. 5 Correlation relationships between the physicommechanical test parameters.

Table 6 Models' performance metrics.

Model	Training MSE	Testing MSE	Training RMSE	Testing RMSE	Training R ²	Testing R ²	Training MAPE	Testing MAPE	Training MAE	Testing MAE	Cross-Validation MSE	10-Fold CV MSE Scores
Linear Regression	232.74	213.56	15.26	14.61	0.76	0.75	57.89	71.85	12.03	11.45	228.53	-232.18
Ridge Regression	232.74	213.56	15.26	14.61	0.76	0.75	57.89	71.84	12.03	11.45	228.53	-232.17
Lasso Regression	232.74	213.58	15.26	14.61	0.76	0.75	57.85	71.79	12.02	11.45	228.53	-231.17
ElasticNet Regression	232.79	213.89	15.26	14.63	0.76	0.75	57.33	71.06	11.99	11.42	228.58	-231.17
Random Forest	0.37	0.87	0.61	0.93	1.0	1.0	1.26	2.81	0.34	0.66	0.22	-1.24
Gradient Boosting	10.74	18.74	3.28	4.33	0.99	0.98	14.63	24.56	2.44	3.22	11.33	-14.58
SVR	334.57	300.57	18.29	17.34	0.66	0.64	51.94	78.67	12.84	12.29	351.14	-334.18

MSE of -1.24. The low value indicates that the model generalizes well not only to the training data but also across different subsets of the dataset.

Furthermore, when comparing the MSE values of the RF model (Cross-Validation MSE, Training MSE, and Testing MSE), the expected order (Cross-Validation MSE < Testing MSE < Training MSE) is not observed. This discrepancy can be attributed to the model being trained on a larger portion of data during cross-validation, while the test set likely contains more challenging samples.

In this study, the developed RF-based UCS prediction model was implemented in Python, and the corresponding code has been made publicly available on the GitHub platform to serve users from various disciplines. This approach ensures both the transparency of the model and facilitates the prediction of UCS values using different datasets.

3.3. DISCUSSION

Conventional methods for determining UCS involve direct measurements through laboratory tests conducted under controlled conditions, following international standards such as ISRM, ASTM, and EN. However, due to challenges in sample preparation and the time-consuming nature of these procedures, these methods may not be practical for projects requiring large datasets. To overcome these limitations, empirical approaches and predictive models based on artificial intelligence (AI) have been developed to estimate UCS values. Among AI techniques, ANNs are the most widely used. Compared to traditional empirical methods, ANNs offer superior predictive accuracy and better generalization capabilities (Meulenkamp and Grima, 1999; Ceryan et al., 2013; Sharma et al., 2017; McElroy et al., 2021; İnce et al., 2025). This advantage primarily stems from the nonlinear and complex relationships often observed among rock properties, which can be effectively modeled through the multilayer architecture and activation functions of ANNs. Consequently, higher accuracy predictions are achievable in scenarios where conventional linear modeling techniques fall short. Despite their strengths in capturing complex nonlinear

interactions, ANN-based models also present certain drawbacks, including the requirement for large datasets, limited interpretability, and susceptibility to overfitting. In applied fields such as engineering and geology, transparency and interpretability of the model's decision-making process are of paramount importance. Therefore, integrating developed predictive models into software platforms and making them accessible to users not only enhances the reliability of the models but also facilitates rapid and straightforward estimation of UCS values without reliance on explicit analytical equations.

Recent AI-based models for predicting UCS have reported high correlation coefficients exceeding 0.95 (Khajevand, 2023; Ding et al., 2025; Mohammed et al., 2025). In the present study, the developed RF model achieved a correlation coefficient of 1.0 for both training and testing datasets. This result indicates that the proposed RF model demonstrates excellent predictive performance.

When comparing the RF model developed in this study with the UCS prediction model based on an ANN using surface hardness values of magmatic rocks proposed by İnce et al. (2025), the RF model demonstrated superior accuracy and generalization performance. The predictive capability of the developed RF model was further evaluated using randomly selected samples from datasets of various rock types, including volcanic, pyroclastic, plutonic, sedimentary, and metamorphic rocks, collected by different researchers (Çelik and Çobanoğlu, 2019; Güneş Yılmaz and Goktan, 2019; İnce et al., 2025). The results corresponding to these diverse datasets are presented in Figure 8. The correlation coefficient for the RF model's UCS predictions across these datasets was found to be 0.9414, confirming its robust performance across different rock types.

The main distinction of this study from previous works lies in the use of a RF model to accurately, rapidly, and practically predict the UCS values of rocks, including magmatic, sedimentary, and metamorphic types, based on surface hardness tests (SHR and HL). Additionally, the model's code has been made publicly accessible via the GitHub

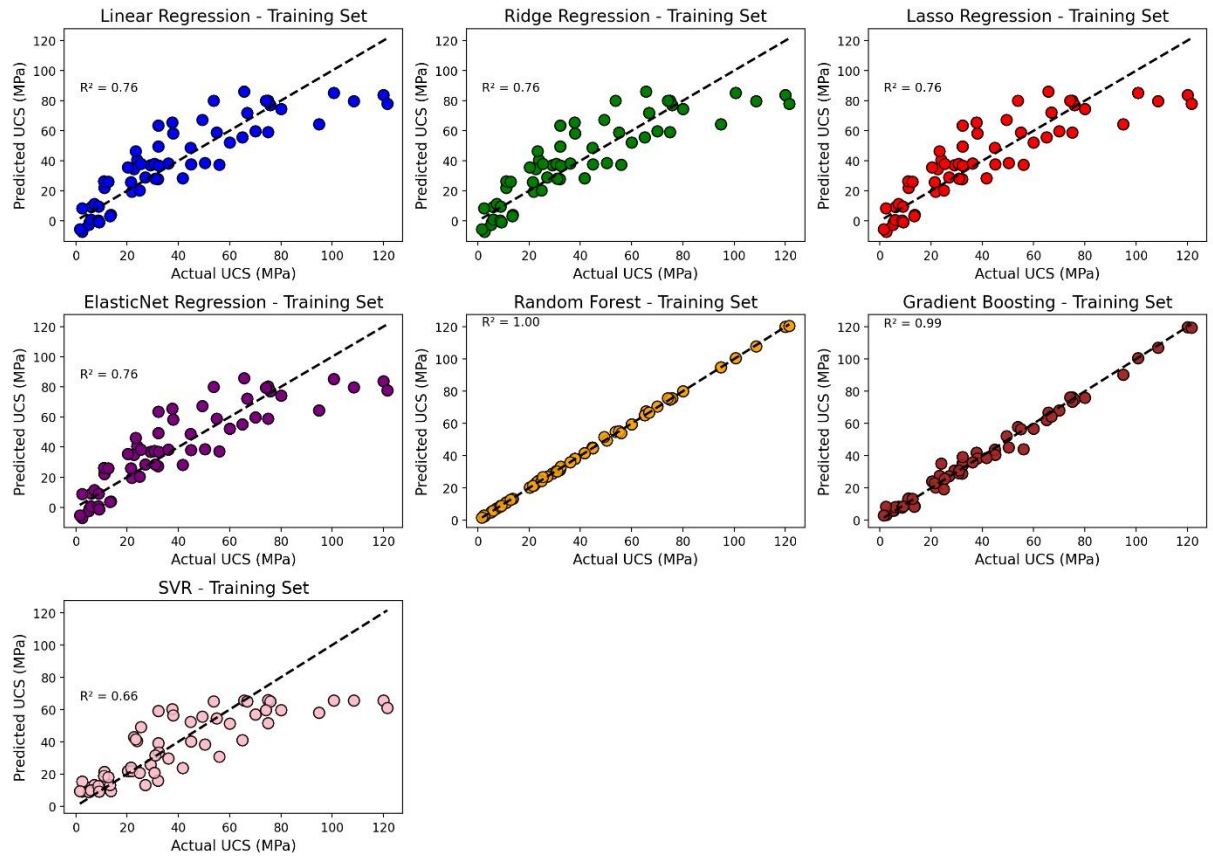


Fig. 6 Training plots of the actual and predicted UCS (MPa) values for the models.

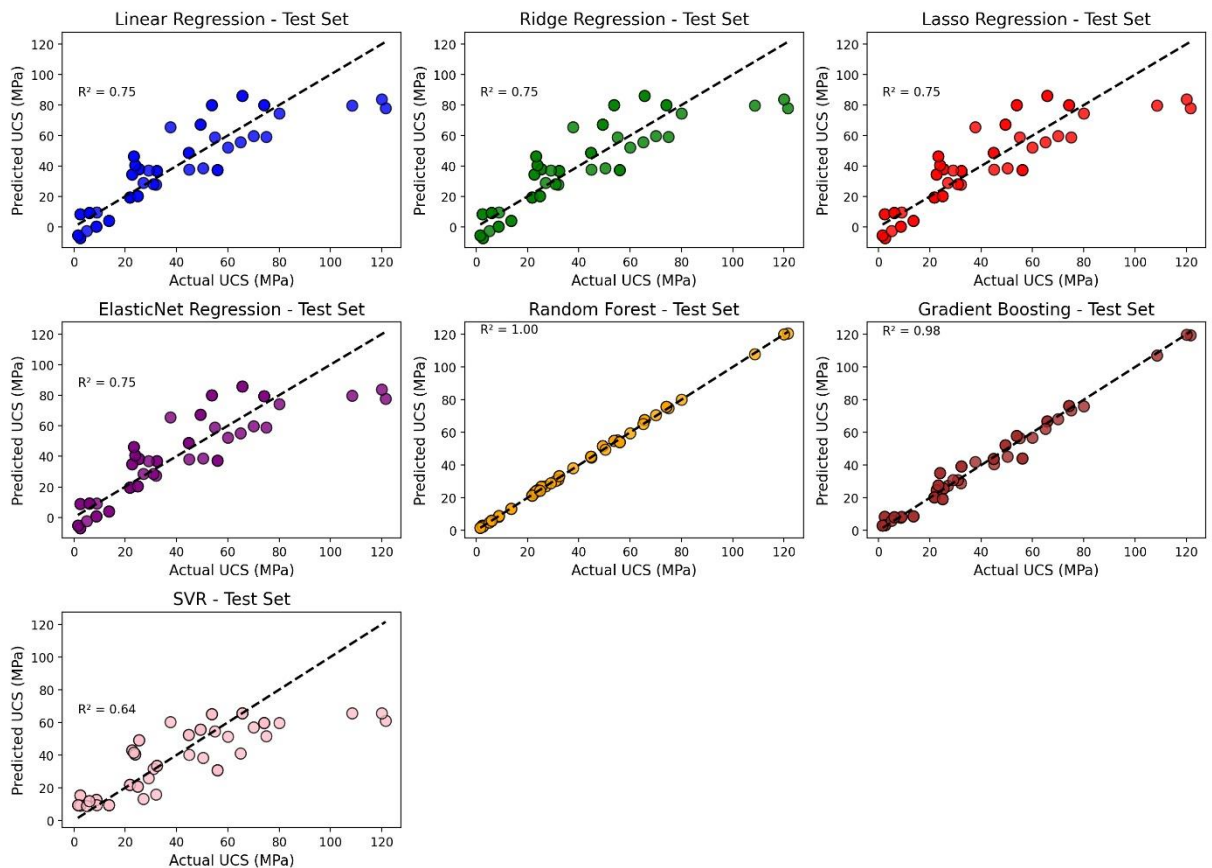


Fig. 7 Test plots of actual and predicted UCS (MPa) values for the models.

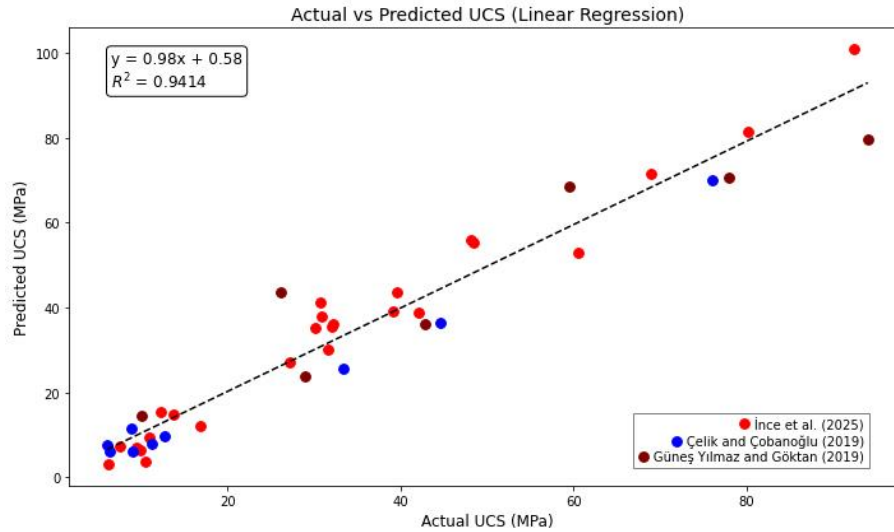


Fig. 8 Prediction performance of RF model on different datasets (Çelik and Çobanoğlu, 2019; Güneş Yılmaz and Gökten, 2019; İnce et al., 2025).

platform, enhancing its usability for a broader user community.

4. CONCLUSIONS

The Uniaxial Compressive Strength (UCS) of rocks is a fundamental parameter in numerous engineering projects. In situations where the UCS value cannot be directly determined, alternative rock properties are utilized for its prediction. In this study, the UCS values of rocks were predicted using non-destructive tests, namely SHR and HL values, through seven different machine learning algorithms (LR, RR, LsR, ENR, RF, GB, and SVR). The primary focus of this study is not on fine-tuning or optimizing machine learning algorithms, but rather on identifying the most effective predictive model for UCS among the existing options. The results obtained are summarized below.

- The correlation relationships between the UCS values and the SHR and HL values, obtained from NDT methods, are 0.75 and 0.71, respectively.
- Among the models developed for predicting UCS values, tree-based models demonstrated the highest performance. The R^2 and MSE values for the RF model on the test set were found to be 1.00 and 0.87, respectively, while the R^2 and MSE values for the GB model on the test set were found to be 0.98 and 18.74, respectively. The cross-validation MSE values for the RF and GB models were found to be 0.22 and 11.33, respectively.
- The R^2 values for the regression-based models (LR, LsR, ENR, RR) on the test set were found to be 0.75.
- It has been observed that tree-based algorithms (RF and GB) outperformed regression-based models (LR, LsR, ENR, RR) in predicting UCS values, demonstrating a better ability to learn the complex relationships within the dataset.
- The SVR model exhibited the lowest performance in predicting UCS values, with an R^2 of 0.64.

It has been observed that it is possible to predict UCS values with excellent accuracy ($R^2 = 1$ or 0.98) using the RF and GB models based on the SHR and HL test results from NDT methods.

DATA AVAILABILITY

The datasets used in this study are available from the corresponding author on reasonable request.

DECLARATION

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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