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ORIGINAL PAPER

EVALUATION OF THE RELATIONSHIP BETWEEN THE SURFACE HARDNESS OF MAGMATIC BUILDING BLOCKS AND UNIAXIAL COMPRESSIVE STRENGTH VALUES WITH REGRESSION ANALYSIS AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Uniaxial compressive strength (UCS) values of rocks are the most important input parameter in rock mechanics and engineering applications. This parameter can be determined by laboratory tests and indirect methods. This study aimed to predict the UCS value with two different non-destructive testing techniques. To this end, the uniaxial compressive strength (UCS) and the values of Leeb hardness (HL) with low application energy and Schmidt hammer rebound hardness (SHR) with high application energy, which are among non-destructive testing techniques, of 95 different magmatic rocks (plutonic, volcanic, and pyroclastic) were determined. Simple regression (SR), multiple regression (MR), and artificial neural network (ANN) methods were employed to predict the UCS value. The models obtained using these methods were compared with each other. It was revealed that the model developed by ANN had the highest correlation number.

1. INTRODUCTION

Uniaxial compressive strength (UCS) of rocks is an important input parameter for rock mass classifications and intact rock failure criteria in engineering projects (slope stability, tunneling, excavation, etc.). The UCS values are determined by the uniaxial compressive strength test performed on core samples taken from rocks in the field and/or core and cube samples prepared in the laboratory. Furthermore, this parameter, which is used for many purposes, can be determined with the help of indirect (point load strength index, Schmidt hammer rebound value, etc.) and empirical approaches. Determining the UCS value in situ and in the laboratory using non-destructive techniques is advantageous in many ways (reduces the time and cost of sample preparation and laboratory testing). While the SHR value, one of the surface hardness tests, is commonly used for indirect determination of the UCS value (Kahraman, 2001; Aydin and Basu, 2005; Sabatakakis et al., 2008; Wang and Wan, 2019), the Leeb hardness value has recently started to be used (Çelik et al., 2020; İnce and Bozdağ, 2021). The relationship between UCS and SHR has been investigated by many researchers using SR (Tugrul and Zarif, 1999; Katz et al., 2000; Aydin and Basu, 2005; Fener et al., 2005; Kılıç and Teymen, 2008; Gupta, 2009; Hebib et al., 2017; Kong and Shang, 2018), MR (Hebib et al., 2017), and artificial intelligence applications (artificial neural network, adaptive-network-based Fuzzy inference system, gene expression programming, etc.) (Heidari et al., 2018; Barzegar et al., 2020; Teymen and Mengüç, 2020; Li et al., 2020; Le et al., 2022). In their study on granitic rocks, Tuğrul and Zarif (1999) indicated a linear relationship between UCS and SHR. In their study conducted using 19 different rock samples, Kılıç and Teymen (2008) found a high correlation coefficient (R^2: 0.935) between the UCS and SHR values. Gupta (2009) investigated the relationships between the UCS values and SHR of the rocks (granite, gneiss, quartzite, and marble) in the Satluj Valley by SR analysis and found the correlation coefficient as 0.91 in granite rocks. In addition to the SHR value, other index (porosity, P-wave velocity) and strength parameters (point load strength index) were used as input parameters to predict the UCS value in MR analysis (Dehghan et al., 2010; Armaghani et al., 2016). Many researchers have used index-strength (dry unit weight, porosity, P-wave velocity, Brazilian tensile strength, point load strength index, slake durability index) values as input parameters to predict the UCS value and made predictions with a high correlation value through artificial intelligence applications (Gokceoglu and Zorlu, 2004; Yilmaz and Yuksek, 2008; Dehghan

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et al., 2010; Jahanbakhshi et al., 2011; Yesiloglu et al., 2013; Madhubabu et al., 2016; Jahed et al., 2018; Heidari et al., 2018; Barzegar et al., 2020; Ceryan and Samui, 2020; Li et al., 2020; Teymen and Mengüç, 2020; Le et al., 2022; Yesiloglu and Gokceoglu, 2022).

There are more limited studies on predicting the UCS value using the Leeb hardness value. In these studies, the UCS value was predicted through SR (Verwaal and Mulder, 1993; Aoki and Matsukura, 2008; Asiri et al., 2016; Su and Momayez, 2017; Corkum et al., 2018; Çelik and Çobanoğlu, 2019; Yilmaz Güneş and Goktan, 2019; Yuksek, 2019; Aldeeky et al., 2020; Çelik et al., 2020; İnce and Bozdağ, 2021), MR (Alvarez-Grima and Babuška, 1999; Gomez-Heras et al., 2020; Benavente et al., 2021) and artificial intelligence applications (Meulenkamp and Grima, 1999; Gomez-Heras et al., 2020) According to Benavente et al. (2021), Leeb hardness is one of the most important variables of regressions, and they indicated that the correlation coefficient increased when it was added to multiple linear equations. In their study, Alvarez Grima and Babuška (1999) developed a fuzzy prediction model using HL, porosity, and density values as input parameters to predict the UCS value. Meulenkamp and Grima (1999) predicted the UCS value of rocks through multiple regression analysis and neural networks methods using rock properties (dry density, porosity, grain size, rock type, and Leeb hardness).

In this study, the UCS values of rocks were predicted by SR, MR, and neural networks methods using the hardness values of magmatic rocks (95 samples) obtained by high (SHR) and low energy (HL) hardness devices.

2. MATERIALS AND METHODS

For this study, 95 samples of magmatic rocks (plutonic, volcanic, and pyroclastic) were collected from the quarries operated in different locations in Anatolia. Table 1 contains the location and rock types of samples used in the study. Homogeneous rock blocks of 20 × 30 × 30 cm in size were collected from the quarries operated for experimental studies. The test samples were prepared in line with the relevant standards to determine the UCS and surface hardness (SHR and HL) properties (TS EN-1936, 2010).

UCS tests were performed on 7x7x7 cm cubic samples in accordance with the standard recommended in TS EN-1926 (2007). The loading rate was applied as 1.0 ± 0.5 MPa/s during the test. This test was conducted five times for each rock, and the average of the obtained values was considered the UCS value of the sample.

The Schmidt hammer hardness test of the samples was performed in line with the standard recommended by ASTM D5873 (2013). An L-type hammer with an impact energy of 0.735 Nm was used in this test. The hammer was applied at right angles to the rock block surface to avoid guiding corrections. Ten measurements were made on each rock sample and averaged to determine the SHR value. Then, the SHR value of the samples was determined by subtracting the rebound numbers, which deviated more than seven units from the average, and re-averaging the values of the remaining ones.

There is no universal standard of the Leeb hardness test for rock materials. This test was carried out on cube samples with a side length of 7 cm, as suggested by İnce and Bozdağ (2021). In the measurements, the D-probe of the Insize ISH-PHB device with an impact energy of 11 Nmm was applied perpendicular to the sample surface. First, the device was calibrated. Then, the measurements were made at 20 different impact points evenly distributed on the sample's surface. The arithmetic mean of the measured values was determined as the HL value for the sample.

Volcanic rocks may present anisotropic properties in relation to flow textures and layering in lava flows, and pyroclastic rocks may show anisotropic characteristics in accordance with layering, the directional arrangement of fragments, and fiamme textures. In relation to these conditions, while performing the tests (SHR, HL, and UCS) on anisotropic rocks, measurements were carried out in the direction perpendicular to the anisotropy planes.

In the present study, the Statistical Package for the Social Sciences version 21 (SPSS Inc.) program was used in the SR and MR analyses. The validity of the developed regression models (SR and MR) was checked by using T test and F-test. While the T test is used to check whether each independent variable is significant in the model, the F-test is used to determine whether the overall regression model is statistically significant. A high value of the F-test indicates that at least one independent variable affects the dependent variable. In the models obtained in both analyses, the p-value was first required to be less than 0.05 for a significance level of 5 % ($\alpha = 0.05$). The statistical significance of the regression model increases when the F-test value is high, and the P-value is very low. Then, among the models meeting this condition, the model with the highest correlation coefficient (R^2) was preferred.

An artificial neural network (ANN) is a system that can learn by imitating the human brain and produce new results from what it has learned. ANN is a structure that is inspired by the brain cells and has an input layer, hidden layers, and an output layer. Studies in which ANNs are used most frequently are classification and prediction studies. Complex models can be developed using nonlinear data (input and output) in prediction studies. In this study, SHR and HL values were used as input data, and UCS was used as output data to develop prediction models. Figure 1 shows the structure of the ANN model employed in the current study.

The training algorithms (trainbr, trainbfg, trainscg, traincgb, traincgf) refer to different

Table 1 The location and type of the rock samples.

Sample	Location	Rock lithologies	Sample	Location	Rock lithologies
1	Erkilet-1/Kayseri	Volcanic	49	Unknow 4	Plutonic
2	Kayseri	Volcanic	50	Unknow 5	Plutonic
3	Sivrihisar-1/Eskişehir	Volcanic	51	Unknow 6	Plutonic
4	Isparta	Volcanic	52	Aksaray	Plutonic
5	Sille 1/Konya	Volcanic	53	Kırşehir	Plutonic
6	Adakale 1/Konya	Volcanic	54	Unknow 7	Plutonic
7	Adakale 2/Konya	Volcanic	55	Unknow 8	Plutonic
8	Madenşehri 1/Karaman	Volcanic	56	Ulaş/Kırıkkale	Plutonic
9	Madenşehri 2/Karaman	Volcanic	57	Kırşehir	Plutonic
10	Niğde	Volcanic	58	Unknow 9	Plutonic
11	Beyşehir/Konya	Volcanic	59	Unknow 10	Plutonic
12	Fasıllar/Konya	Volcanic	60	Unknow 11	Plutonic
13	Çankırı	Volcanic	61	Kayseri-1	Pyroclastic
14	Sille 2/Konya	Volcanic	62	Karayazı-1/Nevşehir	Pyroclastic
15	Eskişehir	Volcanic	63	Kayseri-1	Pyroclastic
16	Kulu/Konya	Volcanic	64	Kayseri-1	Pyroclastic
17	Gölbaşı 1/Ankara	Volcanic	65	Karayazı-2/Nevşehir	Pyroclastic
18	Gölbaşı 2/Ankara	Volcanic	66	Demirciler/Aksaray	Pyroclastic
19	Kayseri	Volcanic	67	Selime/Aksaray	Pyroclastic
20	İscehisar/Afyonkarahisar	Volcanic	68	Gümüşler/Niğde	Pyroclastic
21	Sincan/Ankara	Volcanic	69	Koçcağız/Kayseri	Pyroclastic
22	Sivrihisar 1/Eskişehir	Volcanic	70	Kuruköprü/Konya	Pyroclastic
23	Sivrihisar 2/Eskişehir	Volcanic	71	Emmiler/Kayseri	Pyroclastic
24	Kulu 1/Konya	Volcanic	72	Tomarza/Kayseri	Pyroclastic
25	Kulu 2/Konya	Volcanic	73	Karayazı/Nevşehir	Pyroclastic
26	Yunus Emre/Manisa	Volcanic	74	Ahlat/Bitlis	Pyroclastic
27	Çayırlı/Ankara	Volcanic	75	Karayazı/Nevşehir	Pyroclastic
28	Yunt/Manisa	Volcanic	76	Karayazı/Nevşehir	Pyroclastic
29	İnsuyu/Kayseri	Volcanic	77	Kayseri	Pyroclastic
30	Seydişehir/Konya	Volcanic	78	Mimarsınan/Kayseri	Pyroclastic
31	Erzurum	Volcanic	79	Turanlar/Kayseri	Pyroclastic
32	Gölbaşı 3/Ankara	Volcanic	80	Gökyurt/Konya	Pyroclastic
33	Erkilet/Kayseri	Volcanic	81	Kayseri	Pyroclastic
34	Akören 1/Konya	Volcanic	82	Aksaray	Pyroclastic
35	Akören 2/Konya	Volcanic	83	Kızılören/Konya	Pyroclastic
36	Yükselen/Konya	Volcanic	84	Ardıçlı/Konya	Pyroclastic
37	Sağlık/Konya	Volcanic	85	Afyon	Pyroclastic
38	Erzurum	Volcanic	86	Sille/Konya	Pyroclastic
39	Kaman/Kırşehir	Plutonic	87	Ardıçlı/Konya	Pyroclastic
40	Unknow 1	Plutonic	88	Küçükmuhsine/Konya	Pyroclastic
41	Ispir/Erzurum	Plutonic	89	Gülşehir/Nevşehir	Pyroclastic
42	Unknow 2	Plutonic	90	Nevşehir	Pyroclastic
43	Bergama/İzmir	Plutonic	91	Sadıklar/Konya	Pyroclastic
44	Unknow 3	Plutonic	92	Akören/Konya	Pyroclastic
45	Aksaray	Plutonic	93	Kızılören/Konya	Pyroclastic
46	Çanakkale	Plutonic	94	Kilistra/Konya	Pyroclastic
47	Kırıkkale	Plutonic	95	Karayazı/Nevşehir	Pyroclastic
48	Yaylak/Aksaray	Plutonic			

optimization algorithms used in training artificial neural networks. They are commonly utilized in MATLAB's *Neural Network Toolbox*. Trainbr (Bayesian Regularization Backpropagation) uses Bayesian regularization to optimize the backpropagation algorithm. This method prevents overfitting by controlling the magnitude of weights, and performs well on small datasets and enhances generalization ability. Trainbfg (BFGS Quasi-Newton Backpropagation) is based on the Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimization method and uses an approximation of the Hessian matrix for faster convergence. Trainscg (Scaled Conjugate Gradient Backpropagation) implements the scaled conjugate gradient method for backpropagation. This method does not require second-order derivative information.

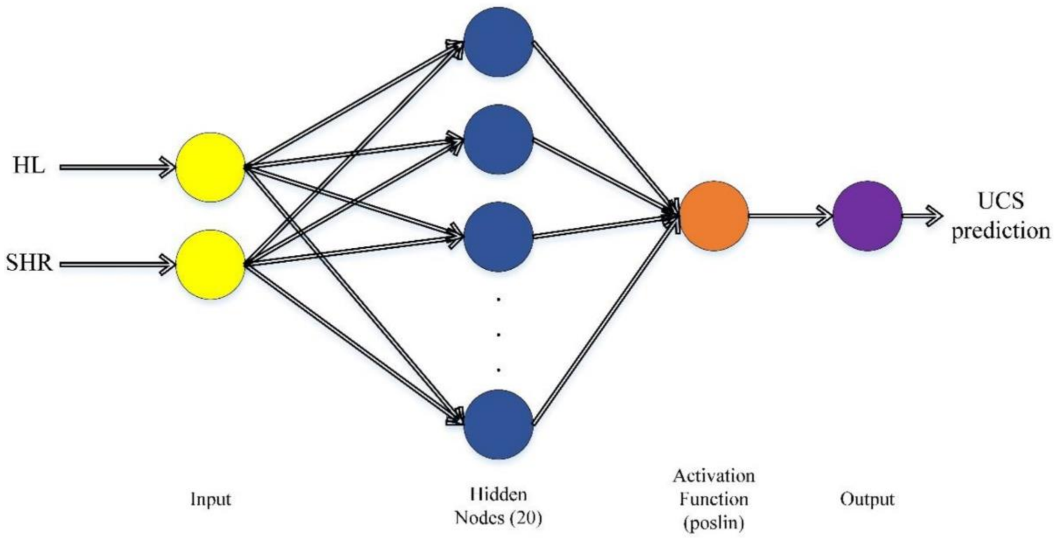

Fig. 1 The structure of the artificial neural network of the developed model.

Table 2 Descriptive statistics of rocks used in the analysis.

Variables	Data	Minimum	Maximum	Mean	Std. deviation	Variance
UCS -MPa	95	6.25	194.60	74.02	48.87	2387.96
SHR	95	12.09	65.30	42.67	12.09	146.28
HL	95	220.00	895.40	666.60	194.66	37893.24

It is more efficient for large datasets. Traincgb (Conjugate Gradient Backpropagation with Powell-Beale Restarts) uses the conjugate gradient method with Powell-Beale restarts. This method achieves faster convergence but may not be efficient for very large datasets. Traincgf (Fletcher-Reeves Conjugate Gradient Backpropagation) is based on the Fletcher-Reeves conjugate gradient method. It minimizes memory usage but may experience performance issues with large networks.

In this study, poslin (Positive Linear Transfer Function - Similar to ReLU) and tansig (Hyperbolic Tangent Sigmoid Function - Tanh) were used as activation functions. Poslin returns zero for negative inputs and the same value for positive inputs. It works similarly to the ReLU activation function and is often used in deep neural networks. Tansig constrains the output to the [−1, 1] range. This method processes negative and positive values separately, making it useful for symmetric problems, and generally provides better generalization compared to the sigmoid function.

3. RESULTS AND DISCUSSION

3.1. STRENGTH AND SURFACE HARDNESS PROPERTIES OF STONE SAMPLES

Table 2 contains the statistical data on the UCS, SHR, and HL properties obtained from the rocks used in the study. The mean and standard deviation values of SHR, HL, and UCS values of each rock are given in Table 3. In the surface hardness values of the samples, the SHR value was between 12.09 and 65.30, whereas the HL value was between 220.00 and 895.40 (Figs. 2a-2b). The UCS value of rocks varied between 6.25 MPa and 194.60 MPA (Fig. 2c). Among the igneous rocks used in the study, anisotropy was observed in samples number 28, 74, and 80. The measurements in these samples were carried out in the direction perpendicular to the anisotropy plane, and the data obtained were used in the modeling. In addition, the standard deviation values of UCS, SHR, and HL values in these samples were also determined to be higher than the general trend. It should be kept in mind that this situation may affect the success of the models predicting the UCS value of rocks showing the anisotropy characteristics.

3.2. DETERMINATION OF EMPIRICAL EQUATIONS

In this study, the relationships between the UCS values of rocks and their surface hardness (SHR and HL) were investigated by SR, MR, and ANN methods.

3.2.1. SIMPLE REGRESSION ANALYSIS (SR)

The correlations between the surface hardness properties (SHR and HL) and UCS values of rock samples were investigated by simple regression (linear, logarithmic, power, and exponential) analyses (Table 4). The best correlations between the UCS values and the surface hardness of samples are presented in Figure 3. The best correlation coefficient between UCS and SHR was acquired from the power function with 0.789. The correlation between UCS and

Table 3 UCS, SHR and HL values of rock samples (mean value ± standard deviation).

Sample No	SHR	HL	UCS MPa	Sample No	SHR	HL	UCS MPa
1	60.24±3.5	781.53±20.1	140.38±5.3	49	54.75±2.2	887.33±9.3	176.00±10.2
2	52.30±2.6	800.93±18.9	111.22±4.6	50	58.34±2.7	880.67±7.8	106.40±9.7
3	48.70±1.9	713.93±15.3	116.33±3.8	51	44.38±1.7	895.40±10.2	96.25±8.9
4	56.29±2.2	809.00±14.3	144.01±7.8	52	63.05±1.8	868.67±5.6	139.25±9.8
5	34.87±1.8	651.67±12.7	63.24±4.6	53	57.15±1.5	871.75±7.9	85.75±7.6
6	36.75±2.2	706.67±15.2	95.39±5.5	54	53.20±1.2	880.00±8.7	92.37±7.9
7	39.28±2.4	772.33±10.2	66.69±3.8	55	57.20±1.8	873.75±6.9	140.31±10.2
8	28.95±1.4	467.33±15.3	21.36±1.9	56	52.78±2.8	867.00±10.2	138.74±13.1
9	31.05±1.5	553.33±12.7	30.79±2.3	57	56.40±1.9	824.50±7.9	154.32±10.2
10	29.45±1.4	575.67±15.0	22.15±1.5	58	52.64±2.0	848.00±11.2	120.67±9.9
11	47.89±1.7	714.00±22.1	100.56±9.3	59	54.31±1.9	889.67±9.6	132.13±10.3
12	43.45±1.6	743.33±17.9	65.20±2.9	60	53.17±1.4	873.00±10.3	120.65±5.9
13	46.84±1.3	759.67±14.6	98.40±4.6	61	30.05±1.4	451.93±14.3	15.09±4.6
14	38.10±1.5	784.00±17.2	60.60±4.9	62	44.18±1.9	501.27±17.6	30.96±3.9
15	36.78±1.2	769.00±19.2	78.20±3.8	63	44.39±2.2	610.33±15.3	40.32±8.6
16	38.79±1.8	791.00±10.1	59.88±4.5	64	22.84±2.6	383.53±16.3	20.26±4.6
17	34.28±2.2	680.33±12.3	67.59±5.6	65	20.56±1.2	300.33±17.6	9.90±1.8
18	42.50±2.0	772.33±14.6	64.94±6.3	66	25.50±1.5	580.33±17.5	48.63±2.2
19	38.75±1.7	768.33±18.3	61.30±5.6	67	22.10±1.6	363.67±13.5	10.55±1.5
20	35.70±1.9	759.00±12.1	63.85±4.5	68	14.80±1.8	258.00±20.1	7.57±1.0
21	41.50±1.8	755.67±10.3	50.68±5.2	69	42.80±2.4	399.67±19.3	31.57±2.9
22	35.90±1.4	674.00±14.5	85.35±5.6	70	49.60±2.7	508.33±14.3	48.38±3.1
23	38.60±1.8	735.67±16.3	71.16±7.1	71	48.80±2.5	488.67±17.6	36.64±2.8
24	42.30±1.4	748.67±16.8	83.63±6.9	72	38.90±1.8	247.33±14.2	27.27±1.8
25	46.30±1.9	799.00±17.6	83.11±4.6	73	30.50±1.3	311.67±15.7	16.86±1.0
26	42.20±1.7	744.00±12.1	91.68±5.9	74	21.20±3.4	324.67±36.9	9.52±1.9
27	34.20±1.4	673.33±19.2	48.13±3.9	75	29.20±1.6	311.67±20.1	24.51±1.5
28	39.50±5.0	768.67±25.6	89.60±7.6	76	31.30±1.9	321.67±19.8	15.68±1.0
29	45.20±1.4	823.00±19.2	78.60±4.6	77	46.25±2.2	720.00±11.4	48.76±2.2
30	46.50±1.9	722.67±11.3	68.97±3.9	78	39.00±2.0	648.67±13.6	32.00±1.0
31	65.30±2.7	892.33±14.6	129.39±7.5	79	47.26±2.1	745.00±14.3	59.71±1.5
32	46.40±2.4	769.67±17.9	100.47±5.5	80	23.50±1.9	378.67±18.3	12.30±2.7
33	61.50±2.2	820.00±14.3	112.79±3.9	81	42.30±3.7	703.33±27.3	42.13±1.5
34	50.40±1.7	795.00±19.3	75.56±4.5	82	34.89±1.8	547.67±15.6	39.62±1.6
35	52.70±1.3	810.00±17.4	80.20±6.6	83	16.70±1.4	220.00±14.3	11.02±0.9
36	41.20±1.5	732.67±16.3	69.80±3.5	84	24.30±1.1	365.00±18.6	13.78±1.1
37	49.60±1.4	693.33±14.5	60.60±2.9	85	32.10±1.8	516.00±18.2	18.95±1.4
38	58.25±2.2	754.00±19.3	66.41±4.5	86	27.90±2.1	357.33±17.6	30.70±2.0
39	54.00±2.6	802.27±7.9	135.4±5.5	87	36.30±1.3	552.67±17.6	32.21±1.8
40	61.67±2.7	872.27±6.9	161.25±4.3	88	33.30±1.9	550.67±15.6	29.78±1.9
41	56.00±1.4	889.4±10.2	167.17±3.9	89	54.30±2.0	800.00±11.6	96.70±7.4
42	54.68±1.6	881.47±7.9	158.96±6.9	90	37.10±1.8	512.33±14.6	39.10±3.0
43	52.24±1.4	825.13±8.3	167.05±8.9	91	33.81±1.4	460.33±19.3	17.78±1.2
44	56.35±1.9	842.00±8.0	123.46±7.7	92	34.80±1.3	525.25±15.3	25.34±1.1
45	62.42±1.7	870.00±7.5	153.80±4.9	93	36.25±1.9	540.75±17.3	30.18±1.0
46	58.24±2.6	861.00±6.9	155.40±5.9	94	18.20±1.1	366.67±13.9	6.25±0.7
47	61.70±2.7	874.60±7.9	194.60±9.8	95	31.60±1.7	298.33±22.9	12.36±0.8
48	53.60±2.1	892.67±7.5	141.56±3.9				

Table 4 Simple regression analysis results between USC and surface hardness values.

	R^2			
Surface Hardness	Linear	Power	Exponential	Logarithmic
SHR	0.717	0.789	0.771	0.646
HL	0.711	0.816	0.858	0.622

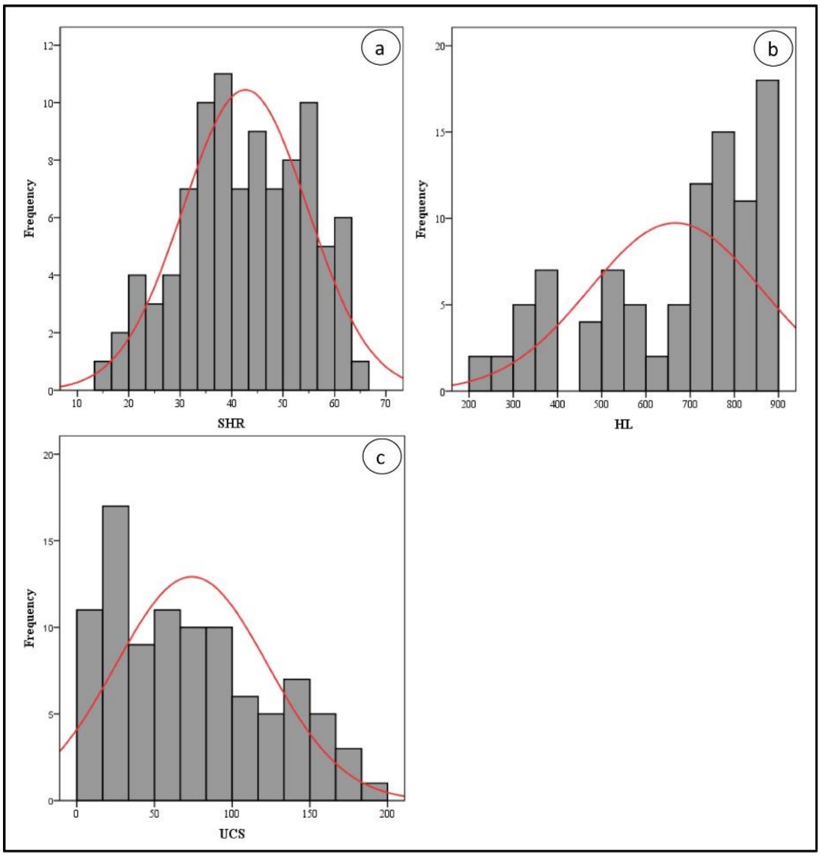

Fig. 2 Histograms of UCS and surface hardness properties: a) SHR, b) HL, c) UCS.

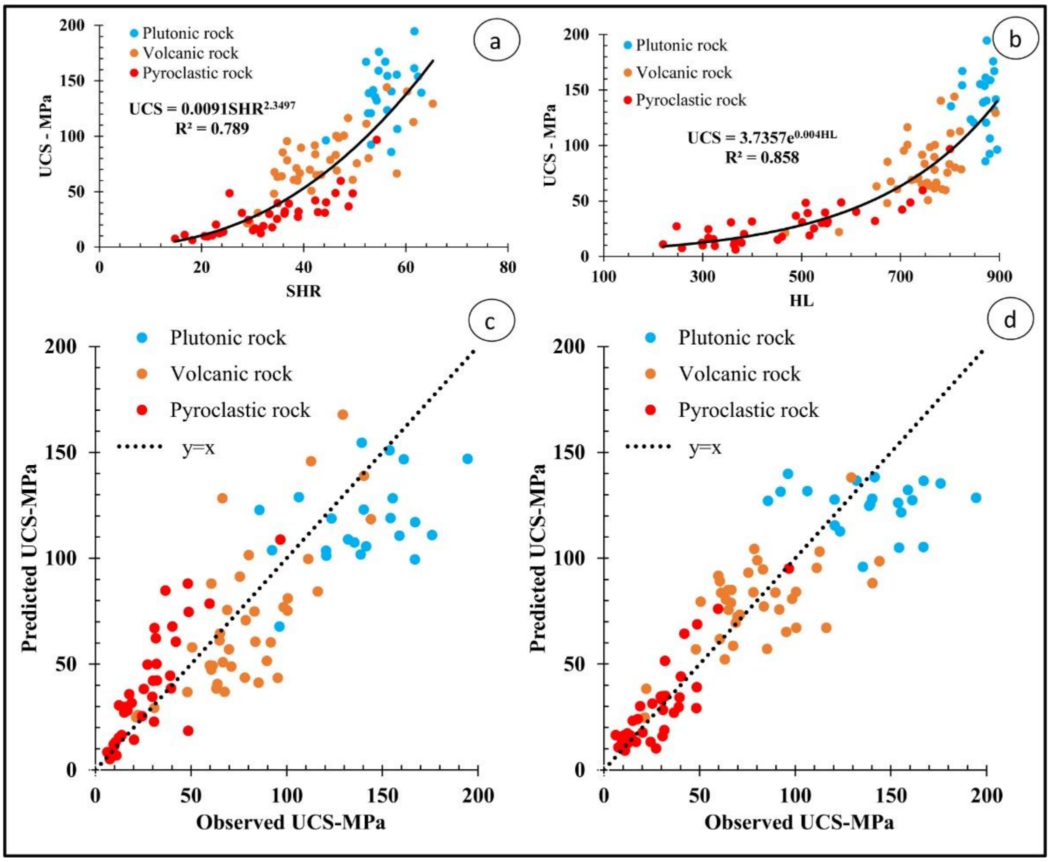

Fig. 3 Relationships between the UCS values of the samples and their surface hardness: a) SHR vs UCS, b) HL vs UCS, c) Estimated UCS from SHR value and measured UCS relationship, d) Estimated UCS from HL value and measured UCS relationship.

Table 5 ANOVA values between USC and surface hardness values.

Surface Hardness	R^2	r	T test	F-test	P<0.05
SHR	0.789	0.888	18.648	347.737	0.000
HL	0.858	0.926	23.663	559.928	0.000

Table 6 Results of MR.

Independent variables	Equation	R^2	F-test	P
SHR, HL	1.908SHR + 0.114HL - 83.083	0.781	164.346	0.000

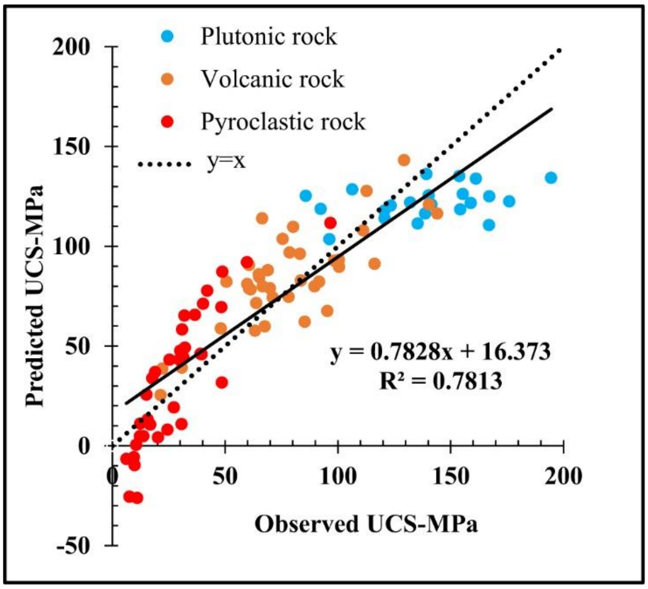

Fig. 4 The relationship between the measured UCS and the UCS predicted from the MR analysis.

HL was obtained with the exponential function, and the R^2 value was found to be 0.858.

The validity of the equations acquired from the simple regression analysis was checked by the analysis of variance, and the results are presented in Table 5. In the SR models that were developed, the highest F-test value and R^2 value were determined in the relationship with HL. A high F value in SR analysis is an important sign that the model is appropriate and reliable. The relationship between the UCS value predicted from both HL and SHR simple regression models and the measured UCS values is presented in Figures 3c-3d. Upon examining these graphs, it was seen that the models developed moved away from the y=x line as the strength values of rocks increased, indicating that the success of the models decreased for rocks with high strength.

3.2.2. MULTIPLE REGRESSION ANALYSIS (MR)

A model predicting the UCS values of rocks through SHR and HL independent variables in the MR analysis was developed in the current study (Table 6). The correlation coefficient value of this model was 0.781, while the F-test value of the model was (164.346). A high F-test value indicates the predictive success of the selected independent variables. However, the correlation coefficient of the model developed through MR was lower than the correlation coefficient of the models obtained from SR. The reason for this was associated with the low linear correlation between the UCS values of rocks and their surface hardness. Furthermore, the MR model negatively predicted the UCS values of rocks with low UCS values (Fig. 4).

3.2.3. ARTIFICIAL NEURAL NETWORK (ANN)

ANN is a method that has been commonly used to predict nonlinear data for a long time. There are many parameters (number of iterations, training and activation functions, learning rate, number of hidden nodes, number of hidden layers), which affect the training of prediction models created with ANN.

This study attempted to yield the best results by changing some parameters to increase the model's success in the training phase. The parameters used in the training phase of the model are presented in Table 7.

The models were trained using the prepared dataset and tested with two different test sets. The first test set was created by setting aside 30 % of the prepared dataset, which consists of 95 samples, as the test set. The second test set was composed of

Table 7 Training phase parameters.

Parameters	Values
Number of iterations	1000
Training function	Trainbr, trainbfg, trainscg, traincgb, traincgf
Activation function	Poslin, Tansig
Number of hidden layers	1
Number of hidden nodes	20,50,80

Table 8 Best results for the training and test data.

Model	Number of hidden nodes	Activation function	Train R^2	Test R^2
Model 1	20	poslin	0.808	0.931
Model 2	20	tansig	0.786	0.553
Model 3	50	poslin	0.716	0.724
Model 4	50	tansig	0.770	0.479
Model 5	80	poslin	0.719	0.743
Model 6	80	tansig	0.924	0.102

19 samples obtained from another study (Çelik and Çobanoğlu, 2019). During the training phase, different training and activation functions, as well as different numbers of hidden nodes, were tested, and the results were compared. The ANN model was trained using 70 % of the prepared dataset with a 10-fold cross-validation process. The results obtained from the training process are presented in Table 8. As a result of the tests, the best training function was found to be “trainbr.” The best activation function was determined to be “poslin.” “Trainbr” is based on its ability to prevent overfitting through Bayesian regularization, making it particularly suitable for small to medium-sized datasets. This method optimizes the trade-off between network complexity and generalization, leading to improved performance compared to other training algorithms. Similarly, “poslin” was determined to be the best activation function based on empirical results. As a piecewise linear function, it avoids issues such as vanishing gradients, making it effective in certain regression and classification tasks.

As seen in Table 8, the best training result was found to be 0.924. However, considering the test result of the same structure, the test success was 0.102. While evaluating the results of ANN structures, the test results are required to be higher than the training results. The failure to meet this condition is known as overfitting and is undesirable. Considering this condition, the best result where the test result was higher than the training result was the first structure where the number of hidden nodes was 20 and the transfer function was poslin. In the first structure, the correlation coefficient for the training set was 0.808 (R: 0.899), whereas the correlation coefficient for the test set was 0.931 (R: 0965).

Figure 5 shows the graphs obtained from the model developed with the ANN approach. Upon examining the prediction success of the ANN model for the entire sample set, the R^2 value was found to be 0.847 (R: 0.920). The success of this model was based on the selected independent variables. Among the variables, the SHR test with high impact energy is more reliable in high-strength rocks, while the HL test using a low-energy probe is associated with yielding more sensitive results in low-strength rocks. With this feature, the developed ANN model may provide significant advantages in predicting the widely varying UCS value.

The developed ANN prediction model was tested with a different data set and cross-validation to assess the generalizability of the results. As seen in Figure 5, the test results on the model trained with cross-validation indicate that the ANN model predicts the UCS value with high accuracy. In this case, since the training and test data were derived from the same dataset, achieving high accuracy is an expected outcome. To evaluate the predictive performance of the model on a different dataset, a second test was conducted using data from 19 magmatic rocks obtained from another study (Çelik and Çobanoğlu, 2019). The obtained result is presented in Figure 6. As a result of this test, the model’s prediction accuracy was found to be 0.9479. Here, the model demonstrated consistent performance across both test procedures, indicating its potential applicability to other datasets.

As stated by many researchers, using ANN to predict the UCS value of rocks can provide higher prediction success and better generalization than statistical methods (Meulenkamp and Grima, 1999; Ceryan et al., 2013; Sharma et al., 2017; McElroy et al., 2021). However, ANN has some limitations. ANNs require a substantial amount of labeled data for effective training. This is because neural networks learn by adjusting their weights iteratively, and a small dataset can lead to overfitting, where the model memorizes training examples rather than generalizing patterns. In fields where data collection is expensive

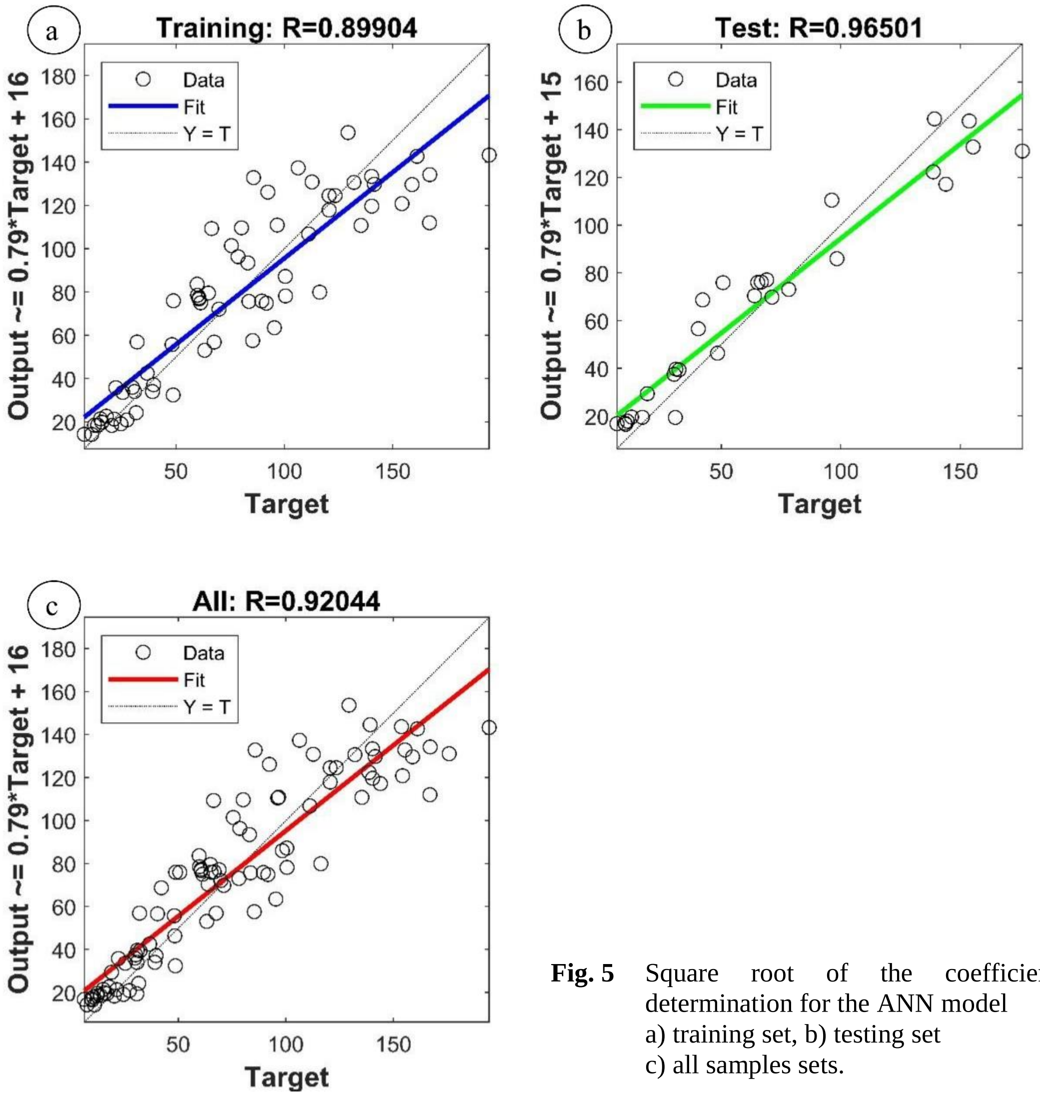

Fig. 5 Square root of the coefficient of determination for the ANN model
a) training set, b) testing set
c) all samples sets.

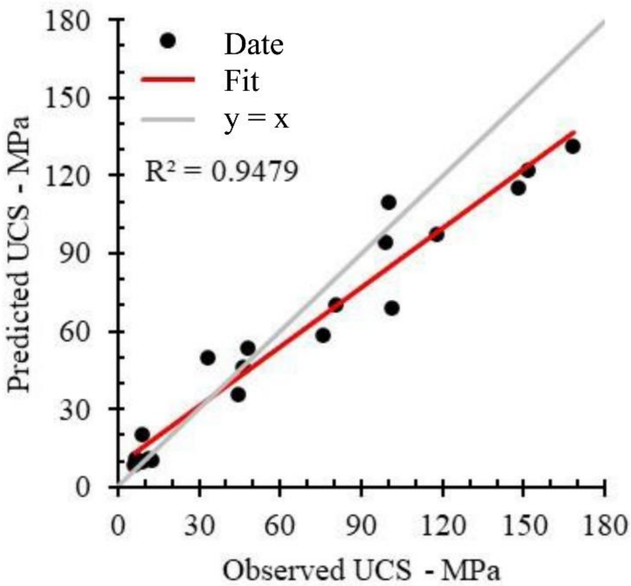

Fig. 6 Prediction performance of the developed model on the dataset (19 samples) obtained from Çelik and Çobanoğlu (2019).

or time-consuming (e.g., geological studies of magmatic rocks), this limitation becomes a significant challenge. Compared to traditional statistical methods or simpler machine learning models, ANNs demand high computational power and long training times, especially for deep architectures. This is due to the extensive number of parameters that need optimization, making training inefficient for large-scale problems without specialized hardware (such as GPUs). If the dataset is small or not diverse enough, ANNs tend to overfit, learning noise and irrelevant details instead of general patterns. Regularization techniques like dropout, weight decay, or Bayesian regularization (e.g., Trainbr) can help mitigate this, but they do not fully eliminate the need for large, high-quality datasets.

In the prediction of UCS with ANN, physical, strength, mineralogical, and textural parameters of rocks are generally used as input parameters. The most important difference of this study from previous studies is its success in predicting the UCS value using SHR and HL parameters, which are non-destructive testing (NDT) parameters that can be obtained in situ and in the laboratory, as input parameters. Using this developed ANN model, the UCS values of igneous rocks can be estimated quickly, practically, and with high accuracy through non-destructive tests such as SHR and HL.

4. CONCLUSIONS

The results of this study can be summarized as follows:

- The uniaxial compressive strength of rocks is one of the most important input parameters in geotechnical and rock mechanics studies. Hence, it is quite important to develop UCS value prediction models in rock mechanics and engineering studies. To this end, 95 building stone samples consisting of pyroclastic, volcanic, and plutonic rocks cropping out in different regions of Turkey were collected. Using the surface hardness (SHR and HL) of these samples, models obtained from SR, MR, and ANN approaches were developed to predict UCS values.
- The highest correlation coefficient (R^2: 0.858) was acquired between the HL value in predicting the UCS value by a simple regression method.
- In predicting the UCS value with the MR model, the R^2 value was 0.781, while the F-test value was 164.346. It was revealed that this model failed to predict the UCS value of rocks with low strength.
- In the ANN model, the R^2 values for training, testing, and all samples were 0.808, 0.831, and 0.847, respectively. Additionally, the prediction performance of the developed model was evaluated using a separate test set. The model's prediction accuracy was determined to be high (0.94). This is evidence that the developed model can be used for different sample sets.
- The ANN model was observed to be quite successful in predicting the UCS value by using the surface hardness values of rocks. By using in-situ and laboratory-measured surface hardness values, the developed model can be used to rapidly, practically, and non-destructively determine the UCS values of rocks.

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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