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ORIGINAL PAPER

Mechanical and Physical Based Artificial Neural Network Models for the Prediction of the Unconfined Compressive Strength of Rock

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Abstract Basalt rocks as building stones were used in many historical buildings in Jordan, and maintenance of these buildings is usually required with time. As part of the effort to collect the necessary information that is needed for future works in repair/strengthen the basaltic structures against any possible future damage. The dry density, Ultrasonic Pulse Velocity, Schmidt Hammer Rebound test, Brazilian Tensile Strength Test, Slake durability, and Point Load test were recorded for specimens tested in the lab to develop indirect methods of estimating the rocks Unconfined Compressive Strength (UCS). Simple regression (SR) analyses were performed to establish correlations between UCS and the results of each above-mentioned rock indices. The SR results showed that a regression model with multiple inputs is needed. In this study, the Back Propagation-Artificial Neural Network (BP-ANN) approach was utilized to predict the USC of Basalt Rock. Two ANN models were developed; one using the physical properties of rocks and the other one using the mechanical properties of rocks. Part of the data collected was used to train the ANN, and a set of independent data was used to validate the developed model. The performance of the ANN model in predicting UCS was compared to that of Multivariate Regression (MVR). The obtained results showed that the ANN model gave higher prediction performance compared to other models. A sensitivity analysis for the developed ANN model was performed to verify the importance of each input. The prediction of UCS can be used to design the proper conservation and repair/strengthen strategies that will allow dealing with the current conditions and the future natural hazards to which these structures are exposed.

Keywords Basalt rock · Historic buildings · Unconfined compressive strength (UCS) · Artificial neural network (ANN) · Multivariate regression (MVR)

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1 Introduction

Basalt as a building stone was used in many historical and ancient cities in Jordan. However, many of these heritage structures are susceptible to damage by different environmental events such as earthquakes. Therefore, parts or sometimes the entire of these un-retrofitted structures were damaged extensively during significant seismic events, while others showed better performance (Bani-Hani and Barakat 2006). The engineering properties of these structures are an essential input in the stability analysis of these structures to analyze the risk and to define the necessary repair/strengthening requirements. For the structural stability analysis, the compressive strength is the main input parameter to describe the structural behavior in any numerical analysis to be performed on the desired structure (Vasanelli et al. 2016).

The UCS test is an expensive and time-consuming test that requires intact core samples (Momeni et al. 2015), and it is not always possible to obtain the appropriate core samples, especially in weak, foliated, weathered and fractured rocks, or not allowed in the historical buildings (Karakuş and Akatay 2013; Azadan and Ahangari 2014; Fakir et al. 2017; Heidari et al. 2018; Jing et al. 2020). As a result, the determination of the UCS through correlation with non-destructive, simple tests that require minimal to no sample preparation became a more desired approach (Dinçer et al. 2004; Yilmaz and Civelekoglu 2009; Monjezi et al. 2012). Different prediction models using regression techniques were developed to predict the UCS from simple or non-destructive tests such as Porosity (η), dry density (γ), Ultrasonic Pulse Velocity (V_P), Point Load Index ($Is_{(50)}$), Brazilian tensile strength (BTS), Schmidt Hammer Rebound hardness (SHR), slake durability index (SDI), shore Scleroscope hardness, and Brinell hardness tests, etc. (Yaşar et al. 2004; Shalabi et al. 2007; Sharma and Singh 2008; Kılıç and Teymen 2008; Yurdakul et al. 2011; Singh et al. 2012, 2017; Karaman and Kesimal 2015; Endait and Juneja 2015; Fereidooni 2016; Wang et al. 2017; Heidari et al. 2018; Fereidooni and Khajevand 2018; Kong and Shang 2018; Seif et al. 2018; Umrao et al. 2018; Wang and Wan 2019).

However, using regression models in UCS prediction may result in several shortcomings. As such, these models predict the mean values only, and this will result in overproduction or under-prediction of the low and high UCS values, respectively (Meulenkamp and Grima 1999; Majdi and Rezaei 2013; Momeni et al. 2015). Moreover, these models are not suitable to deal with highly nonlinear problems (Majdi and Rezaei 2013). Recently, the soft computing methods; Artificial Neural Networks (ANNs), adaptive network-based fuzzy inference system (ANFIS), Genetic Programming (GP), and regression trees have been utilized in developing predictive models for complex problems.

ANN is a non-parametric model with a high capability to learn complex nonlinear relationships among variables implicitly. ANN with backpropagation (BP) learning algorithm is a well-established method for solving different classification and forecasting problems (Han and Yin 2018). Researchers used ANN to address various problems for many applications in Civil Engineering. In geotechnical engineering, in particular, Maji and Sitharam (2008) developed two ANN models (using Feed Forward Back Propagation (FFBP) and Radial Basis Function (RBF) methods) for prediction the elastic modulus of jointed rocks considering different joint configurations and confining pressures.

Ferentinou and Fakir (2017) used ANN to develop a correlation between UCS and rock basic indices such as $Is_{(50)}$, γ, BTS, and lithology for sedimentary and igneous rocks. Heidari et al. (2018) used multiple linear regression (MLR) and the Sugeno-type fuzzy algorithm for UCS prediction for different types of rocks using rock indices (block punch index (BPI), $Is_{(50)}$, SHR and Vp). Both the fuzzy model and the MLR analyses gave a better prediction for the UCS than the SR. Umrao et al. (2018) used ANFIS for UCS and modulus of elasticity prediction for sedimentary rocks. Experimental data for density, η, and Vp were used in the proposed model. Jahed Armaghani et al. (2015) developed three different nonlinear techniques; Nonlinear Multiple Regression (NLMR), ANN, and ANFIS to predict the UCS of rocks for a tunnel project in Malaysia. Data of SHR, $Is_{(50)}$, Vp, and UCS properties of granitic rocks were used in the analysis. The analysis results showed that the ANFIS model predicted the UCS with the highest accuracy among the other models.

In this study, six physical and strength parameters, including γ, Vp, SDI, SHR, BTS, and $Is_{(50)}$, were determined in the laboratory. Correlations between the test results for these indirect indicators with UCS test results were assessed by simple, Multiple Regression Analysis, and ANN. Two ANN models utilizing the physical and mechanical properties of the tested rock have been developed through this study. The developed models can be used for UCS prediction in the restoration/ rehabilitation of existing heritage structures.

2 Materials and Methods

2.1 Materials

During the Roman period, basalt stones were used to build many historical and ancient cities in Jordan such as Um-Qais city located to the north of Jordan, Qaser Al Mashta, Um- Al Jimal (east of Al-Mafraq), Qaser Al Hallabat and Qastal (south of Jordan), and Qasr Al-Azraq (Tarrad et al. 2012), as presented in Fig. 1. Basalt rock covers about 11% of Jordan's area (about 11,400 km^2), as shown in Fig. 2, particularly in the northeast of Jordan (HarratAl-Sham) and northwest (Harrat Irbid) (AL-Malabeh 2003; Abu-Mahfouz et al. 2016).

To establish the necessary physical and mechanical properties for future stability analysis of these structures, 56 block samples with a minimum dimension of approximately 30 cm, were collected from the neighboring areas with similar in lithology to the nearby basalt historic buildings and cities. From each boulder, three cylindrical rock core specimens with diameter 64.0 mm and length of 130.0 mm were prepared to obtain a length/diameter ratio of 2:1, according to

(A) (B) (C) (D)

Fig. 1 Picture of some basalt historic buildings and cities in Jordan A) Um- Qais city located to the north of Jordan, B) Qasr Al-Azraq, C) Qaser Al Hallabat and Qastal, D) Um- Al Jimal (east of Al-Mafraq)

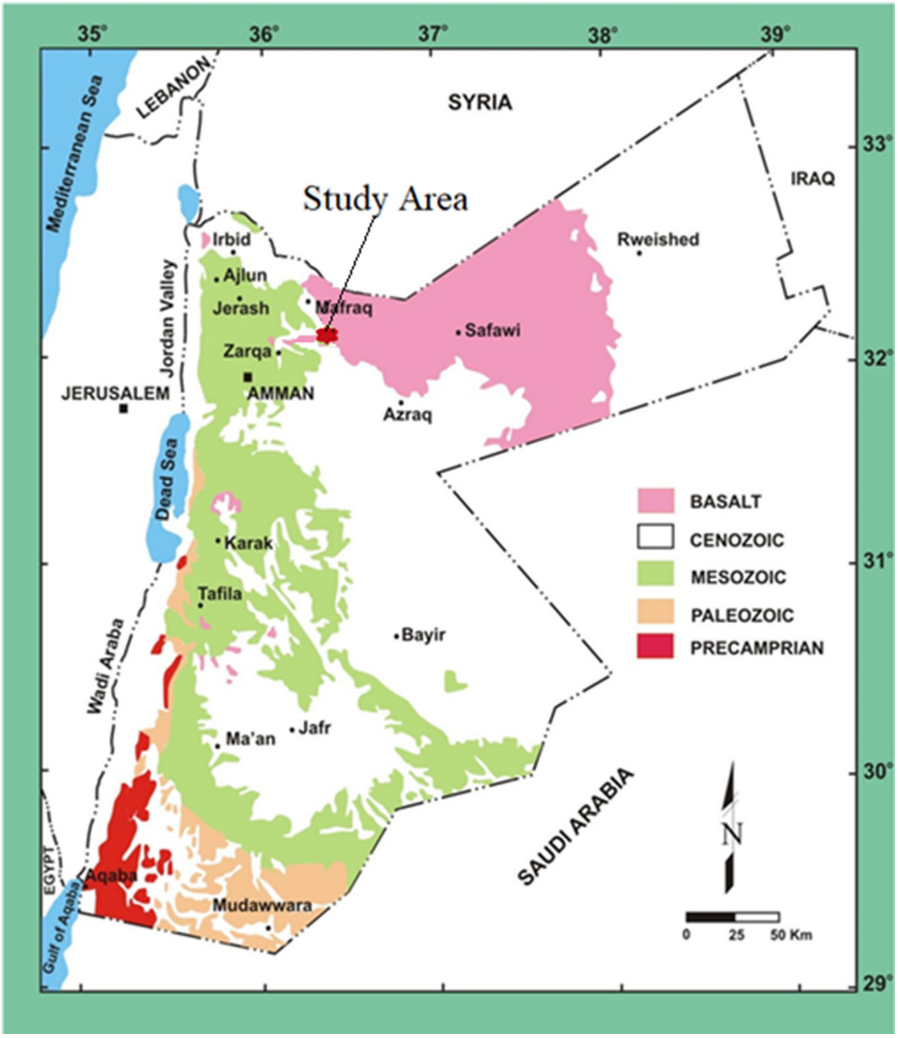

Fig. 2 General Geological Map showing the distribution of the primary rocks types in Jordan (Alnawafleh et al. 2013)

ISRM (2007) and ASTM D4543. The extracted cores were ground to remove all surface irregularities.

2.2 Experimental Tests

X-ray Fluorescence Spectrometry (XRF) was used to determine the dominant and minor oxides in these rock samples, and the XRF results are presented in Table 1. The XRF analysis shows that the majority of oxides are Augite and Feldspar, whereas Hematite, Calcite, and Zeolite occur in little amounts. Based on results the basalt rock in the study is classified as magic alkaline basalt rock.

Figure 3. is showing a sample of a microphotograph of minerals components. Plagioclase is the most abundant minerals with a lath-like phenocryst

Table 1 XRF analysis of studied basalt samples

Mineral	Percentage, %
SiO_2	40.0–43.0
Fe_2O_3	13.2–14.3
Al_2O_3	11.8–12.7
CaO	9.9–11.8
MgO	9.15–9.80
TiO_2	2.80–3.30
Na_2O	0.62–2.50
K_2O	0.53–1.30
P_2O_5	0.57–0.65
MnO	0.19–0.22

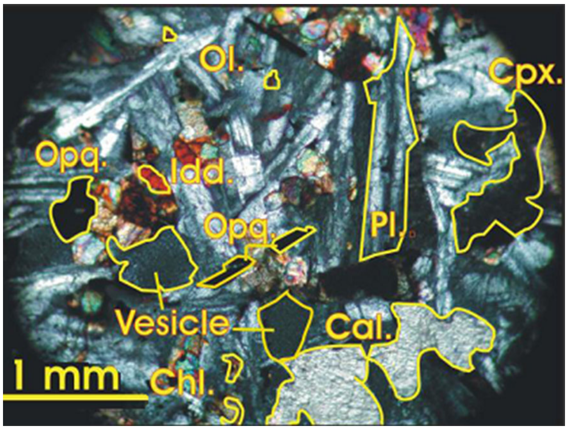

Fig. 3 Microphotograph of mineral components. (Ol.: Olivine; Idd.: Iddingsite; Pl.: Plagioclase; Cal.: Calcite; Mag.: Magnetite; Cpx.: Pyroxene and Chl.: Chlorite) (Al-Zyoud 2012)

shape. Pyroxene is second abundant minerals, and lower amounts of Olivine, Iddingsite, Calcite, Magnetite, and Chlorite were also found (Al-Zyoud 2012).

The specimen's dry weight (γ) was determined after drying the specimens at 105 °C for 24 h. The (γ) values were calculated by dividing the specimens' dry weight by its volume. The V_p test measures the velocity of the primary wave through the rock. However, the (Vp) of rocks is influenced by the particle sizes (Vajdová et al. 1999). The ISRM (2007) recommended that wave travel distance should be greater than ten times the particle size. Since Basalt rocks is an extrusive with fine-grained textures, therefore, the length of the sample satisfies the ISRM (2007) recommendation. Two transducers with 54 kHz frequency were used in this study to perform the V_p test according to both ISRM (2007) and ASTM specifications.

ASTM D 5731 Standard Test Method was adopted to conduct the $Is_{(50)}$ test on core samples irregular lumps resulted from broken cores. The obtained results of the point load test had been corrected to a diameter of 50 mm.

Slake durability tests were performed based on ISRM specifications to measure the resistance of the rock to disintegration after drying and wetting cycles. During the test, ten basalt pieces, each weighing between 40 and 60 g with a total weight of about 500 g, were used to conduct the test.

Since the Schmidt hammer rebound test is a cheap, nondestructive, quick, and easy to apply in either site or laboratory that can be used in rock strength assessment. Therefore, many researchers developed numerous correlations between SHR, either linear or nonlinear, with UCS and E_t for a different type of rocks (Kılıç and Teymen 2008; Gupta 2009; Karaman and Kesimal 2015; Fereidooni 2016; Singh et al. 2017; Heidari et al. 2018; Fereidooni and Khajevand 2018; Kong and Shang 2018; Wang and Wan 2019). The BTS tests were conducted on 1:2 for length/diameter ratio on core specimens according to ASTM D3967 with a rate of the applied load of 200 N/s.

The ASTM D-7012 procedure was adopted to conduct the USC tests using a computerized MTS compression machine (Fig. 4) on core specimens with flat, smooth, and parallel ends with length to diameters ratio of 2:1 at an applied rate of 0.2 MPa/s.

3 Results and Discussion

3.1 UCS Prediction from Simple Regression (SR) Analysis

SR analyses were used to investigate the type of correlation between UCS (dependent variable) and each one of the index parameters (independent variables), where the SPSS program was utilized to

Fig. 4 Uniaxial compression test using the MTS machine

develop the regression models. However, parametric statistical methods, such as regression analysis, the analysis of variance, and hypothesis testing, require that the dependent variable is normally distributed.

Two tests, Kolmogorov–Smirnov test, and Shapiro–Wilk test were used by SPSS to check for normality. Table 2 presents the results for both tests. 0.05 was selected as the significance level throughout this study; the Null hypothesis: The data is normally distributed. Table 2 shows that the calculated p-values of both tests are greater than 0.05, so the null hypothesis is retained at the 0.05 level of significance. Therefore, the two tests indicated that the data obtained for the dependent variable (UCS) is normally distributed, and the appropriate parametric tests can be used (Table 3).

Different sorts of regression relationships such as linear, power, exponential, and logarithmic relationships between the UCS and rock indices were used to select the best relationship to fit the UCS of the rock. Both the coefficient of determination (R^2) and Root Mean Square Error (RMSE) were used in this study to evaluate the performance of these relationships.

$$R^2 = \frac{\left[\sum_{i=1}^{N}\left(M_{i}-\overline{M}\right)^2\right] - \left[\sum_{i=1}^{N}\left(M_{i}-P_i\right)^2\right]}{\left[\sum_{i=1}^{N}\left(M_{i}-\overline{M}\right)^2\right]} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(M_i - P_i\right)^2} \tag{2}$$

where M_i is the measured UCS values, P_i is the predicted UCS values obtained from the predictors, $\overline{M}$ is the average of the M_i, and N = number of the data points.

Figure 5 shows the developed equations to predict the UCS based on different independent variables.

Table 2 Tests of normality for the dependent variable (USC)

Tests of normality						
	Kolmogorov–Smirnova test			Shapiro–Wilk test		
	Statistic	df	Sig.	Statistic	df	Sig.
UCS	0.062	50	0.200	0.989	50	0.919

df degree of freedom, *sig*. significant level (0.05 as chosen in this study)

Table 3 shows the selected equations for UCS prediction based on the highest obtained R^2 values, and the lowest RMSE values compared to other equation types. As can be seen, the SR analyses give good correlation coefficients between UCS and most of the independent variables. The $Is_{(50)}$ resulted in the best estimation of the UCS.

From the above analyses, it is noticeable that the tested samples showed low variability of properties, and the performances of most indices were reasonably good in predicting UCS. However, to obtain higher R^2 (lower RMSE), Multivariate Regression Analysis (MVR) could be used to establish a predictive model for predicting UCS amongst relevant rock properties.

3.2 Multivariate Regression Model (MVR)

MVR is an extension to SR by considering multiple independent variables to obtain the best-fit equation with the highest R^2 and lowest RMSE values between the input and output variables. The general form of the MVR model can be written as follows:

$$y = b_0 + b_1x_1 + b_2x_2 + \ldots.. + b_nx_n \tag{3}$$

where, y is the dependent variable (UCS), $b_{0,1,2\ldots n}$ are the regression parameter coefficients, and $x_{1,2\ldots n}$ are the independent variables. In this study, the statistical package for Social Science (SPSS) program was used to develop the MVR models.

Multicollinearity is a common problem in multiple regression analyses, where a high correlation between independent variables exists. The possible multicollinearity of the input independent variables was evaluated in the MVR model using the variation influence factor (VIF). In this study, all the proposed models were checked for multicollinearity, a VIF value of 8 was consider to check for multicollinearity problem (Hines and Montgomery 1990).

For regression models, the value of R^2 can be improved by increasing the number of parameters (Feng and Jimenez 2014). However, fitting too many variables could result in overfitting problems (Yang et al. 2019). Overfitting results from adding too many independent variables that account for more variance but add nothing to the model. In this study, two separate predictive models were developed. One model was developed to predict the UCS based on rock physical indices (γ, V_p, and SDI), and the other model was developed based on rock's mechanical

Table 3 The developed equations for estimating UCS

Predictor	Range	Mean	Std. Dev	Equation	R^2	RMSE
Dry density (γ), gm/cm^3	2.59–2.74	2.66	0.034	UCS = 413.49 γ−1015.6	0.71	9.26
P-wave velocity (Vp), m/s	4364–5920	5163	403.0	UCS = 194.93 ln(Vp)−1579.5	0.81	7.48
Slake durability index (SDI), %	97.9–99.5	98.6	0.41	UCS = 34.98 SDI−3363.7	0.74	8.88
Schmidt hammer rebound number (SHR)	32–46.9	40.5	2.97	UCS = 0.01 SHR $^{2.45}$	0.81	7.43
Brazilian Tensile Strength (BTS), MPa	2.11–14.33	7.57	2.59	UCS = 5.92 BTS + 41.63	0.82	7.31
Point load index ($Is_{(50)}$), MPa	4.71–7.3	5.99	0.60	UCS = 26.46 $Is_{(50)}$−72.11	0.87	6.20

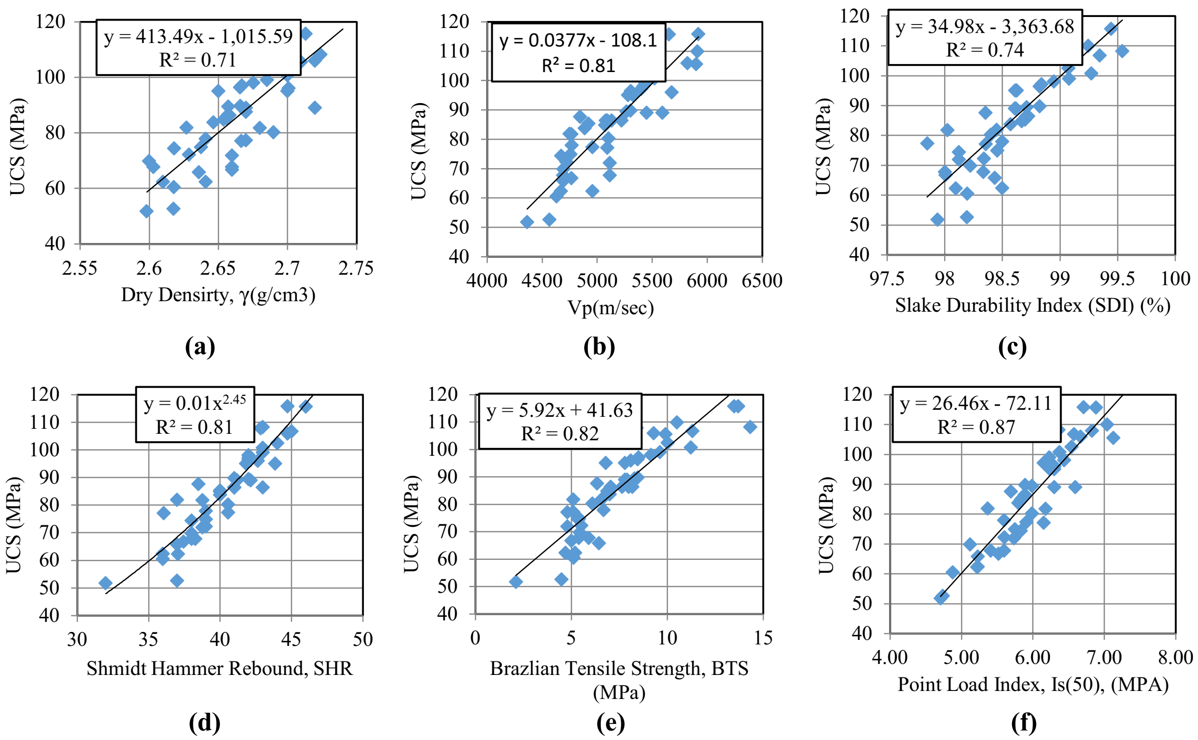

Fig. 5 The developed equations for estimating UCS using **a** Dry density (γ), **b** P-wave velocity (Vp), **c** Slake durability index (SDI), **d** Schmidt hammer rebound number (SHR), **e** Brazilian Tensile Strength (BTS), and **f** Point load index ($Is_{(50)}$)

strength indices (BTS, SHR, and $Is_{(50)}$). These variables were selected for MVR analysis because they are the most common rock's indices that are used to estimate the UCS for the rock. The two developed MVR models are shown in Table 4.

For the same set of data, higher R^2 was obtained using MVR compare to SR. In MVR, the dependent variables work together in a combined manner, whereas the other independent variables take care of any shortcoming of any other independent variable (Mishra and Basu 2013). This explains the benefits of using MVR over SR.

As can be seen, the results are statistically meaningful, but to develop higher performance models, ANN models are built to develop a more accurate model for UCS prediction**.**

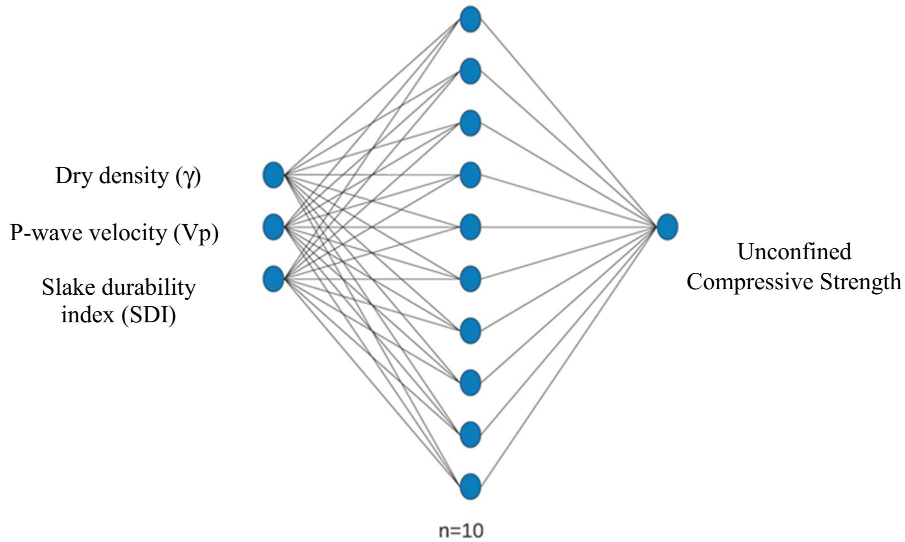

Fig. 6 Physical Properties—Based ANN model

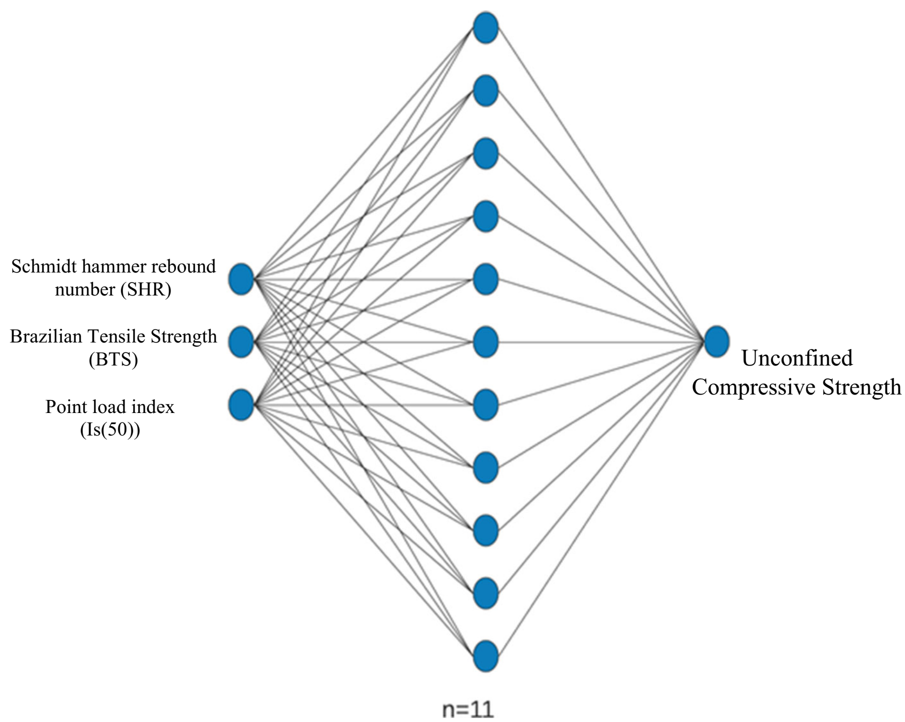

Fig. 7 Mechanical Properties—Based ANN model

Table 4 MVR equations in addition to the coefficient of correlation for the two models

Model	Developed a relationship	R^2	RMSE
Physical MVR model	UCS (MPa) = $-1994.4 + 24.32\text{x}SDI + 0.033\text{x}V_p - 182.8\text{x}\gamma$	0.92	4.65
Mechanical MVR model	UCS (MPa) = $-57.65 + 14.08\text{x}Is_{(50)} + 2.39$ BTS $+ 1.03$ SRH	0.95	3.67

3.3 ANN Models

Artificial Neural Network offers superior capabilities over the traditional regression methods in capturing the nonlinear relationship between variables.

The ANN analysis was performed for the data set used in the MVR model to form correlations for UCS (dependent variable) prediction using six independent variables ($ls_{(50)}$, BTS, SRH, SDI, Vp, and γ). Two ANN models were developed to predict the UCS. The first model was based on experimental results of the physical properties, including (γ, V_P, and SDI). The second model was based on the mechanical properties of the rock, namely ($Is_{(50)}$, BTS, and SHR). The experimental data were divided into two parts, training and testing data. The training data were used to teach the ANN the nonlinear relationships between the input parameters (Physical and Mechanical measures) and output node; the UCS. The validation data were used to validate the developed ANN models. In addition to the two ANN models, two MVR models based on physical and mechanical properties were developed using the same data sets, as was discussed before.

The back-propagation learning (BP) algorithm was used for supervised learning to train the weights of the multilayer feed-forward neural network using gradient descent. BP algorithm searches for the minimum value of the error function by adjusting the weights. The gradient of the error function is calculated with respect to the neural network's weights. Tangent-Sigmoid activation function was used in the hidden layer. The final ANN models are shown in Figs. 6 and 7.

An ANN model and a multivariate regression model (MVR) were developed, as discussed earlier. Because of the highly nonlinear correlation between the UCS and the physical and mechanical properties, a total of three layers have been used, including one for input, one hidden layer, and one nodded output (UCS) layer. The weights and biases of both ANN models are listed in Tables 5 and 6, respectively.

Table 7 shows the results of R^2 and RMSE for all models developed for the training/testing/validation data used in MATLAB. It is clear from the results that both the mechanical and physical ANN models were able to predict the experimental results with high accuracy.

The R^2 and the RMSE values for both models of 0.99, 0.94, 1.54, and 1.73 suggest that the ANN models learned the relationship between the physical and the mechanical properties of rock and the UCS with a slight advantage for the Mechanical over the physical ANN model. Figures 8, 9 show the performance of the results obtained from the Mechanical ANN and the Physical ANN models for the data employed to train, test, and validate the models in MATLAB. The ANN results of the experimental UCS (x) plotted against the predicted UCS (y) are also shown. The two figures show a great agreement with the 45° line of equality, which represents the points where Y equals X. Both ANN models learned and predicted the experimental data very well.

For further investigation in the capability of the developed ANN models in predicting the UCS, a set of 10 independent data points that have not been used in the development or validating of the previously discussed four ANN models were used to predict the UCS values. Figure 10 shows the results of the ANN models for independent data. It is evident from the figure that the results of ANN models for the UCS values are in good match with the experimental results. ANN models seem to give a precise prediction for the rock's UCS using both the physical and mechanical properties.

Table 8 below presents the RMSE values for the 10 points independent data used to verify both ANN models. The RMSE values suggest that ANN models are a very powerful tool for predicting the UCS from unseen physical and mechanical data points. Once again, the Mechanical ANN model seems to give a slightly better prediction for USC that the ANN model.

Although ANN is often labeled as a ''black box'', several methods have been used by researchers for identifying the input variables contribution. In the present study, the Connection weight approach presented in Oña and Garrido (2014) has been used to identify the importance of the input variables in UCS prediction. Based on the weights listed in Tables 5, 6, the importance and relative ranking of input variables of both ANN models are shown in Table 9. It can be concluded that Dry Density (γ) and Schmidt hammer rebound number (SHR) are ranked as the most important parameters while P-wave velocity and Brazilian Tensile Strength (BTS) as the least important.

As shown in Table 9, among input parameters, the most influential parameters on the UCS are DD for the ANN physical model and SHR for the ANN mechanical model. This may be attributed to the fact that the

Table 5 Weights and biases of the Physical Based ANN model

Hidden neuron	Weights: input to the hidden layer			Hidden to output layer		Bias
	Dry density	P-wave velocity	Slake durability index	Hidden neuron	Weights	
1	−0.6971	3.0235	−4.5906	1	−0.5342	0.3240
2	−8.7934	−7.5433	−4.3911	2	−1.5688	−1.5011
3	−4.7989	−0.6850	−14.8862	3	1.3680	−1.9231
4	−6.2844	5.4093	11.1425	4	5.2494	0.5806
5	7.2995	−17.0102	−8.6992	5	7.6934	0.6555
6	2.4658	0.5486	−13.9914	6	1.5433	−0.8179
7	7.3245	12.1211	14.6807	7	3.8575	6.8060
8	−0.2850	2.4199	3.9030	8	1.9290	−9.7247
9	−0.5170	3.5282	−1.2143	9	1.5529	−3.5177
10	−6.2410	2.6945	1.9630	10	−6.2101	−0.6029
				Output Node		−3.3099

Table 6 Weights and biases of the Physical Based ANN model

Hidden neuron	Weights: Input to the hidden layer			Hidden to output layer		Bias
	Schmidt hammer rebound number (SHR)	Brazilian Tensile Strength (BTS)	Point load index (Is(50))	Hidden neuron	Weights	
1	0.0675	−1.2094	2.6636	1	0.6361	−3.1854
2	−0.5977	1.2037	−3.5213	2	0.8166	−1.1535
3	3.8984	−0.6817	−2.2937	3	0.7989	−1.4188
4	−1.4841	−2.0155	−2.0079	4	0.4550	1.8586
5	1.8826	0.0575	2.2472	5	0.8822	−0.5922
6	−2.2747	0.6363	2.6171	6	1.1925	−0.1768
7	−0.8491	2.2973	2.1769	7	1.2736	−1.6350
8	−2.5660	−2.4149	−1.3277	8	0.4634	−0.7980
9	3.4539	0.0518	−1.0712	9	1.5613	2.2550
10	−1.5399	0.9431	−1.3893	10	-0.2002	−3.7176
11	−3.2118	0.5033	−0.1577	11	-0.7191	−3.0240
				Output Node		0.3680

Table 7 Performance of ANN models

Model	R^2	RMSE
Mechanical ANN model	0.99	1.54
Physical ANN model	0.94	1.73

dry density indicates the state of compactness of the rock (Momeni et al. 2015). As shown in the ANN analysis, the UCS is much more strongly correlated with SHR and Is(50) than with BTS. This may be attributed to the fact that in BTS, the mode of failure is different from the UCS (Mohamad et al. 2015). The same results were obtained by Jing et al. (2020) when as sensitivity analysis was performed to show the relative influence of the *V*p, *I*s(50), and SHR on the UCS, where the results show that the SHR was the most influential parameter on the UCS prediction.

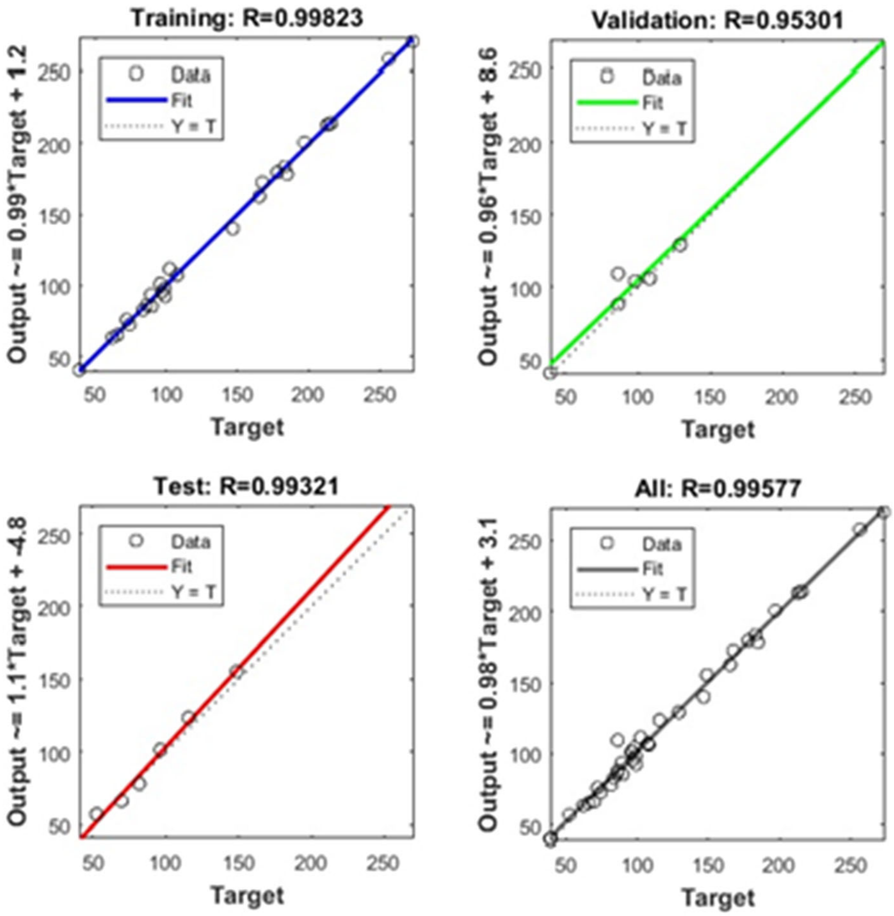

Fig. 8 Mechanical ANN Model performance results

4 Summary and Conclusion

Extensive laboratory tests for the estimation of UCS were conducted on 56 Basalt sample sets. The experimental program included UCS, $Is_{(50)}$, BTS, SHR, SDI, Vp, and γ measurements. A reasonable relationship was found between inputs and output by performing an SR analysis. However, the results of the SR analysis showed that there is a need to propose models with multiple inputs. To predict UCS indirectly from multiple inputs, two MVR and ANN models were proposed. In the first model, the laboratory tests of rock physical properties (γ, Vp, and SDI) were used as inputs for the network while the UCS value set to be the output. Whereas in the second proposed predictive model, the laboratory tests of rock mechanical properties ($Is_{(50)}$, BTS, SHR) were used as inputs for the network while the UCS was set to be the output. The following conclusions can be drawn from this work:

(1) Both Multivariate Regression analyses and the ANN exhibited better predictive performances than SR analyses as far as the estimation of UCS from rock physical and mechanical indices with higher advantage for the ANN models over the MVR models as it can be seen by higher R^2 and lower RMSE.
(2) Both physical and mechanical properties based-ANN models can be used to predict the UCS value of Basalt rock with high accuracy. However, the mechanical based-ANN model showed slightly better performance in predicting the UCS of rock over the physical based-ANN model.
(3) ANN was able to predict the nonlinear relationship between the UCS value and both of the mechanical and physical measures of Basalt Rock.
(4) Sensitivity analysis was performed to find the relative effect of input parameters used in the USC prediction model. The obtained results suggest that

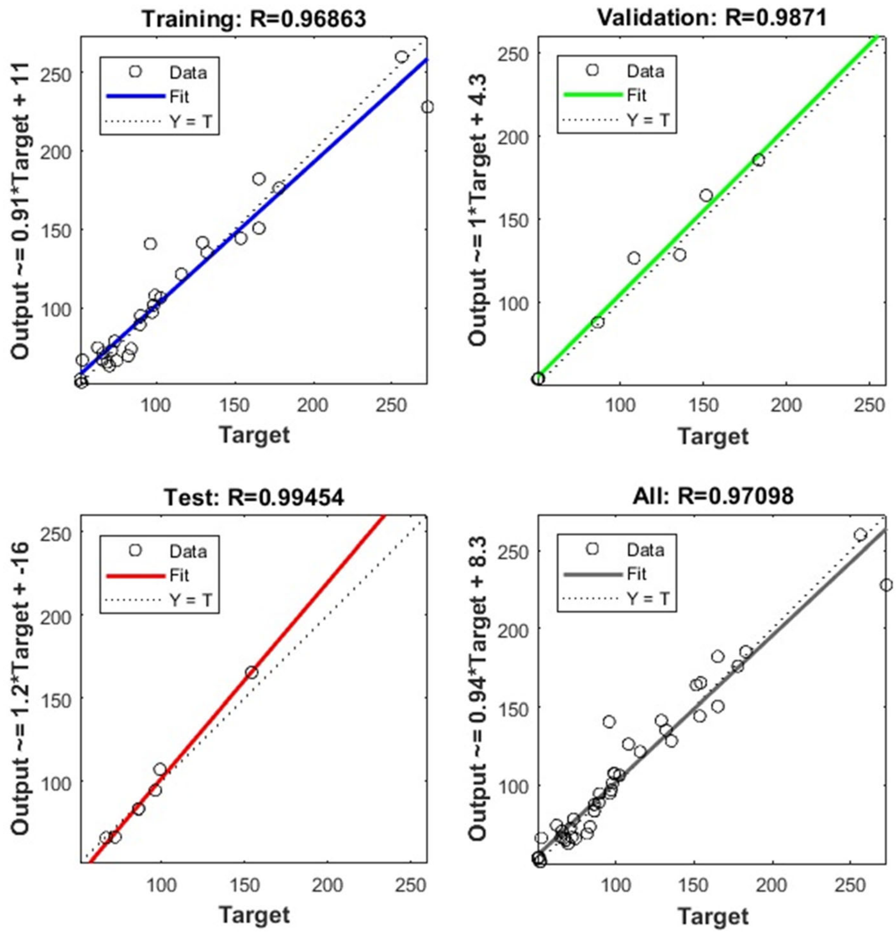

Fig. 9 Physical ANN Model performance results

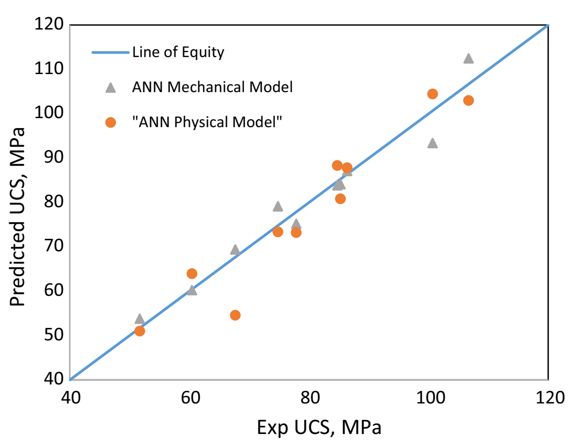

Fig. 10 Independent data results for both the Mechanical ANN models and the Physical ANN model

Table 8 Independent data RMSE comparison

Model	ANN
Mechanical models	0.59
Physical models	0.74

all input considered that SHR and γ have the highest influence on the prediction of the UCS values.

(5) The Artificial Neural network's high capabilities of learning and capturing the nonlinear relationship explains the superiority of ANN models over the MVR models in predicting the UCS values.

Table 9 Sensitivity analysis results based on the connection weight approach

Physical ANN model			
Variable name	Dry Density	P-wave velocity	Slake durability index
Importance	100.2	−50.2	9.03
Relative ranking	1	3	2
Mechanical ANN model			
Variable name	Schmidt hammer rebound number (SHR)	Brazilian Tensile Strength (BTS)	Point load index (Is(50))
Importance	6.68	0.898	2.05
Relative ranking	1	3	2

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