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Using multivariate regression and multilayer perceptron networks to predict soil shear strength parameters

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Abstract. The most significant soil parameters that are utilized in geotechnical engineering projects' design and implementations are soil strength parameters including friction (ϕ), cohesion (c), and uniaxial compressive strength (UCS). Understanding soil shear strength parameters can be guaranteed the design success and stability of structures. In this regard, professionals always looking for ways to get more accurate estimations. The presented study attempted to investigate soil shear strength parameters by using multivariate regression and multilayer perceptron predictive models which were implemented on 100 specimens' data collected from the Tabriz region (NW of Iran). The uniaxial (UCS), liquid limit (LL), plasticity index (PI), density (γ), percentage of fine-grains (pass #200), and sand (pass #4) which are used as input parameters of analysis and shear strength parameters predictions. A confusion matrix was used to validate the testing and training data which is controlled by the coefficient of determination (R^2), mean absolute (MAE), mean squared (MSE), and root mean square (RMSE) errors. The results of this study indicated that MLP is able to predict the soil shear strength parameters with an accuracy of about 93.00% and precision of about 93.5%. In the meantime, the estimated error rate is MAE = 2.0231, MSE = 2.0131, and RMSE = 2.2030. Additionally, R^2 is evaluated for predicted and measured values correlation for friction angle, cohesion, and UCS are 0.914, 0.975, and 0.964 in the training dataset which is considerable.

Keywords: geotechnical engineering; multivariate regression; shear strength; soil materials

1. Introduction

Because the majority of structures are constructed on soil ground, understanding soil's geotechnical characteristics are essential in civil engineering (Azadi *et al.* 2022). These characteristics are known as soil shear strength and soil stiffness parameters which are frequently linked to the failure of the ground and building collapse (Azarafza *et al.* 2019, 2020, 2022a, b, c). Generally, the soil's capacity to resist failure under shear stress is referred to as soil shear strength. It plays a crucial role in the geotechnical design and stability analysis of structures, including foundations, slopes, retaining walls, embankments, and bridges (Sharma *et al.* 2021). Understanding and accurately predicting soil shear strength is vital in geotechnical engineering because it directly affects the stability and safety of structures that rely on the ground for support. Soil shear strength tells us how well the soil can resist sliding or failure when it's under pressure, which is key for designing foundations, retaining walls, and slopes. If these parameters are not properly assessed, there's a risk of underestimating potential soil failures, which could lead to structural damage, costly repairs, or even life-threatening situations. That's why getting these measurements right is essential to ensure that structures are stable, safe, and capable of withstanding expected loads (Karumanchi and Nerella 2022). The soil type, texture, water content, stress history, and consolidation rate can all have an impact on a soil's shear strength (Venkatesh and Bind 2020). The cohesion, friction, and interlocking between particles determine the soil's shear strength, or shear resistance, under various loading conditions which directly affected the soil structure's durability and stability (Azarafza *et al.* 2022a). In the estimation of soil shear strength, the main parameters included density, water content, overburden pressure, loading condition, consolidation rate, soil mineralogy, and void ratio which determine by laboratory tests like direct shear, triaxial, and torsion, as well as field tests like vane shear, cone penetration, and plate loading (Moayedi *et al.* 2020).

Cohesion, friction angle, and dilatancy angle are just a few of the strength parameters that can be learned from these tests (Azadi *et al.* 2022). Typically, the effective stress and soil parameters including, cohesion and internal friction angle, are used to calculate the soil shear strength which is used in various geotechnical assessments like foundation analysis, bearing capacity, or settlements in different scale designs. The shear strength parameters serve as the foundation for the most prevalent approaches to determining bearing capacity, such as the Vesic and Hansen approaches (Murthy 2002, Fang 2013). These parameters can be used for stability analysis of slopes, embankments, and the design of retentions regarding soils' failure (Abramson *et al.* 2001, Nanehkaran *et al*. 2021).

Understanding the soil shear strength goes to providing detailed geotechnical designs. So, it requires that these parameters are estimated accurately. Although experimental

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Table 1 A summary for related works on ANN application in soil engineering characteristics

References	Method	Geo-unit	Target	Database	R^2	Error rate
Das and Basudhar (2008)	MLP	Clayey soil	c, ϕ	-	-	-
Baykasoglu *et al.* (2008)	MLP	Limestone	c, ϕ	-	-	-
Canakci *et al*. (2009)	MLP	Basalt	UCS, UTS	-	-	-
Kahraman *et al.* (2009)	MLP	Rock	UCS, E	105		-
Gunaydin *et al*. (2010)	MLR	Clay	UCS	85	0.71–0.97	-
Dehghan *et al*. (2010)	MLP	Rock	UCS, E	10	0.64	-
Yilmaz and Kaynar (2011)	MLP, RBF	Clayey soil	Swelling	215		-
Khanlari *et al*. (2012)	MLP, MLR, RBF	Clay	c, ϕ	200	0.87	2.91
Mohammadi et al. (2014)	MLP	Clay	c, ϕ, E	100	0.93	-
Abdalla *et al*. (2015)	MLP	Clayey soil	c, ϕ, β	160	0.99	-
Torabi-Kaveh and Sarshari (2019)	MLR, MNR, SVR, GPR, regression trees, ET	Clay	c, ϕ, σ_c, RMR, H, NB	-	0.93	-
Zhang *et al.* (2020)	SVM, HYFIS, MLR, CART, and CIT	Clay	UCS, c, ϕ	145	0.972	-
Nanehkaran *et al.* (2022)	MLP, k-NN, DT, RF	Clayey soil	c, ϕ, H, β, γ_d	70	0.93	0.1
Zhang *et al*. (2022)	MLP	Clay	ϕ	162	0.79	-
Dinarvand and Ardakani (2022)	SVM, MLP	Silty	c, ϕ	36	0.98	-
Cemiloğlu *et al*. (2023)	SVM	Limestone	UCS	120	0.967	0.2006

Note: UTS: uniaxial tensile strength, MLR: multivariate linear regression, RBF: radial basis function, MNR: multivariate nonlinear regression, SVR: support vector regression, GPR: Gaussian process regression, ET: ensembles of trees, σ_c: uniaxial compressive strength of rock mass, H: overburden height, NB: number of installed rock bolts, SVM: support vector machine, HYFIS: hybrid neural fuzzy inference system, CART: classification and regression tree, CIT: conditional inference tree, E: elasticity, k-NN: k-nearest neighbors, DT: decision tree, and random forest, H: slope height, β: total slope angle, γ_d: dry density.

and laboratory approaches provide direct answers from the soil, the existence of uncertainties caused by human errors, non-calibration of the device, sampling problems, high cost of tests, and lack of access to all the soils in the projects' site have caused different approaches should be used to estimate soil shear strength parameters (Pitilakis *et al.* 1999, Germaine and Germaine 2009, Day 2012, Soltanian *et al*. 2024). Empirical correlations and methods are commonly used to estimate the soil shear strength parameters (Murthy 2002). Recently with numerous geotechnical applications, soft computing systems have undergone significant development which is used for shear strength parameters estimations (Mao *et al*. 2023). These methods follow a remarkable accuracy rate to predict the parameters properly (Pham *et al.* 2021). Nguyen *et al.* (2021) investigated and compared the performance of the artificial neural network (ANN), extreme learning machine (ELM), and Boosting Trees algorithms regarding the effect of different ratios of training on testing in predicting soil shear strength. The training/testing ratios had a significant impact on the predictive power of the ANN models, according to their performance. Pham *et al.* (2018) evaluated and compared the performance of multilayer perceptron (MLP), support-vector regression (SVR), genetic algorithm (GA), adaptive network-based fuzzy inference system (ANFIS), and particle swarm (PSO) techniques to predict the strength of soft soils. The results indicated that the ANFIS and MLP have the highest prediction capability. Mohammadi *et al.* (2022) applied various types of ANN models such as MLP to predict friction angle (ϕ) and cohesion (c) from soil-based indexes such as percentages of gravel, sand, silt, clay, Atterberg limits, density, and particle-size analysis results. Zakharov *et al.* (2022) discussed the MLP application for clayey soil's mechanical parameters based on previously established physical properties. According to the result, it appeared that the MLP is a good capability for predict soil properties. Table 1 provides a summary of several researches that conducted on ANN application for shear strength parameters estimations in soils.

The presented study attempted to use MLP and multivariate regression modeling to predict the soil strength parameters. Using such predictive models regarding the ability to work with limited information, archive data across the entire network, able to accept errors, have a spread-out memory, corruption over time, and capacity for parallel processing are considered for assessments. The models were prepared and implemented in Python high-level programming language. It has to be noted that using machine learning techniques like MLP requires several considerations which are known as method limitations. Dependence on hardware, trouble displaying the network, and the network's duration being unknown are some of the basic machine model limitations (Park and Lek 2016). If the proper hardware is available, the model can be run properly and displaying was act functionally. Our aim in this study was to use both algorithms MLP and MR for the indirect evaluation of shear strength parameters. In this study, c, φ, and UCS have been correlated with simple tests and predicted by the models.

Our study enhances current methods, such as traditional correlation techniques, for predicting soil shear strength parameters by incorporating advanced machine learning

Fig. 1 Location of studied region in Iran

models like Multilayer Perceptron (MLP) and Multivariate Regression. These methods improve prediction accuracy by capturing complex, non-linear relationships in the data that traditional methods might overlook. Unlike conventional approaches, which often rely on simplified assumptions and limited variables, our machine learning models can analyze large datasets with multiple influencing factors, leading to more precise and reliable predictions. This advancement provides geotechnical engineers with more robust tools for assessing soil behavior, ultimately improving the design and stability of structures.

2. Materials and methods

2.1 Engineering geologic description of Tabriz soil

Tabriz is the most populated and authentic city in the northwest of Iran, and the capital of the East Azerbaijan Area. The city of Tabriz is situated at 1350 m above ocean level and inside the valley of the Quru-chay between the Sehend volcanic complex Mountains. This Valley closes in the plain and the eastern bank of Urmia Lake (Azarafza and Mokhtari 2013).

Tabriz has a variety of cohesive soils, including clay, silt, and various kinds of yellow, green, and gray marl which has different potential for settlement. The impact of tectonic forces and the activity of faults, folds, and erosion have all contributed to the study area's geomorphology in Tabriz city, in northwest Iran.

River erosion and sedimentation were among the major influences on this region's geological formation. The majority of the rivers and glacial sediments of the Cenozoic and Quaternary formations that make up Tabriz City, which was built on the Tabriz Plain, are young, unconsolidated deposits of varying textures and grades. The Mehranroud, one of this region's most important rivers, cuts through almost all of the studied area (Hooshmand *et al*. 2012). Dense-grained sediments or semi-hard conglomerates are found in other parts of the city, especially in the southern and western parts, on a marl formation with polio-quaternary sand and silt in the middle layers.

2.2 Experimental data preparation

A fundamental component of a geotechnical investigation is laboratory testing which provides direct information about soil and rock materials. The suitable laboratory program will provide enough data to finish a cost-effective design without requiring additional costly tests and samplings (Pitilakis *et al.* 1999, Karumanchi and Nerella 2022). Tests may range from straightforward tests of soil classification to more in-depth tests of strength and deformation, depending on the issues of the project (Moayedi *et al*. 2020). For example, sensitive and high-scale projects require extensive sampling and more tests than low-sensitivity and small-scale projects. Regardless of the project's scale and sensitivity, there are several ground principles that must be considered in all ground investigations. Index tests are the main procedure that willing to conduct on soil materials to specify the geotechnical properties of soil such as strength parameters, classification, and stiffness (Azadi *et al.* 2022).

In this study, samples have been taken from both surface and subsurface soil points (up to 1.3 m) in south part of Tabriz city, which is located in the northwest of Iran. Fig. 1

Table 2 Statistical analysis for studied samples

Statistics	Particle-size (passing %)		Atterberg limits (%)		γ (kN/m^3)	c (kPa)	ϕ (o)	UCS (kPa)
	#4	#200	LL	PI				
Max	99.00	85.17	86.00	48.00	19.74	35.1	35.0	37.20
Min	81.20	21.55	32.00	10.00	16.40	12.0	26.0	6.520
Mean	92.57	47.39	57.41	32.04	18.71	21.6	30.2	21.57
Standard deviation	5.018	16.59	17.04	12.56	0.746	6.11	3.10	5.719
Variance	25.18	27.55	29.06	15.79	0.557	37.4	9.63	32.71
Skewness	-0.40	0.523	-0.06	-0.43	-1.41	0.52	0.25	0.244
Test number	100	100	100	100	100	100	100	100

Table 3 Correlation matrix for input data from geotechnical tests

Parameters	#4	#200	LL	PI	γ	c	ϕ	UCS
#4	1							
#200	0.63	1						
LL	0.37	0.49	1					
PI	0.31	0.52	0.65	1				
γ	-0.12	-0.17	0.03	0.10	1			
c	0.32	0.38	0.49	0.25	0.12	1		
ϕ	-0.45	-0.71	-0.77	-0.62	-0.34	0.19	1	
UCS	0.26	0.31	0.55	0.72	0.79	0.62	0.44	1

is presented the location of the study in Iran and the sampling sites. Although the city is completely covered in recent alluvial sediments, excavations have revealed the presence of conglomerate, sandstone, and marl layers beneath the sediments. Eynali Volcanic Mountain and Sahand Volcanic Complex can be found in the city's northern and southern regions. The samples are provided by hand digging and isolated in the site to control the water content and soil moisture. The samples after taking carried out to a geotechnical laboratory to conduct index lab tests such as particle-size analysis (ASTM D6913), Atterberg limits (ASTM D4318), Density (ASTM D7263), and UCS (ASTM D2166). All tests have been performed according to ASTM instructions and the tests were repeated three times in a row the average of the three tests was reported as the evaluation result. Totally, 100 specimens were collected from the Tabriz region and information on the measurements is recorded as the main database for consideration. The statement of MLP's and MR's capability to estimate soil shear strength parameters is the fundamental premise of the current study. The input parameters selected based on Kayadelen *et al.* (2009) and Khanlari *et al*. (2012) works to increase the model capability, accuracy, and more structured analysis. These selected parameters have a greater impact on shear strength parameters from a geotechnical standpoint. Table 2 provides statistical descriptions of the parameters analyzed. This table also demonstrates that the mean and average values of all parameters are closely correlated. This demonstrates that the experimented samples' statistical distribution of this parameter is nearly normal.

Frequency histograms are also used to display test results to show how many samples were used the tests where results are presented in Fig. 2. This figure indicated that the samples have a nearly normal distribution and are primarily populated between 28 and 31 degrees for friction angle, 37% to 54% for fine grain (≠200), and 95% to 99% for sand (≠4). Cohesion values typically have frequencies between 18 and 24 kPa. The frequency histogram's number of samples for the liquid limit (LL) and plasticity index (PI) indicates the variations are from 40% to 50% for PI and from 32% to 46% for LL. The density values typically range from 18 kN/m^3 to 19 kN/m^3, respectively.

To find out the linear correlation between the variables in this study, a correlation matrix was used. A correlation matrix is a table that shows how different variables are related to each other. The linear relationship between two or more variables is frequently measured using this method in finance and statistics. The strength and direction of the relationship between two variables are indicated by the correlation coefficient, which can be found in any cell of the matrix and ranges from -1 to 1. A correlation coefficient of one indicates that there is a perfect positive relationship between the two variables—that is, that they both increase or decrease simultaneously. A coefficient of -1 indicates a perfect negative relationship, in which one variable rises while another falls. A coefficient of 0 indicates that the two variables do not have a linear relationship. In a variety of fields, correlation matrices are utilized to aid in dimension reduction, identify relationships that can be used to make predictions, and assist in understanding the relationships that exist between variables (Mertler *et al*. 2021). Table 3 is providing the correlation matrix for input data that is willing to use in the modelling process. In an effort to define the degrees of linear relationships between all variables, the bivariate correlation method was applied to

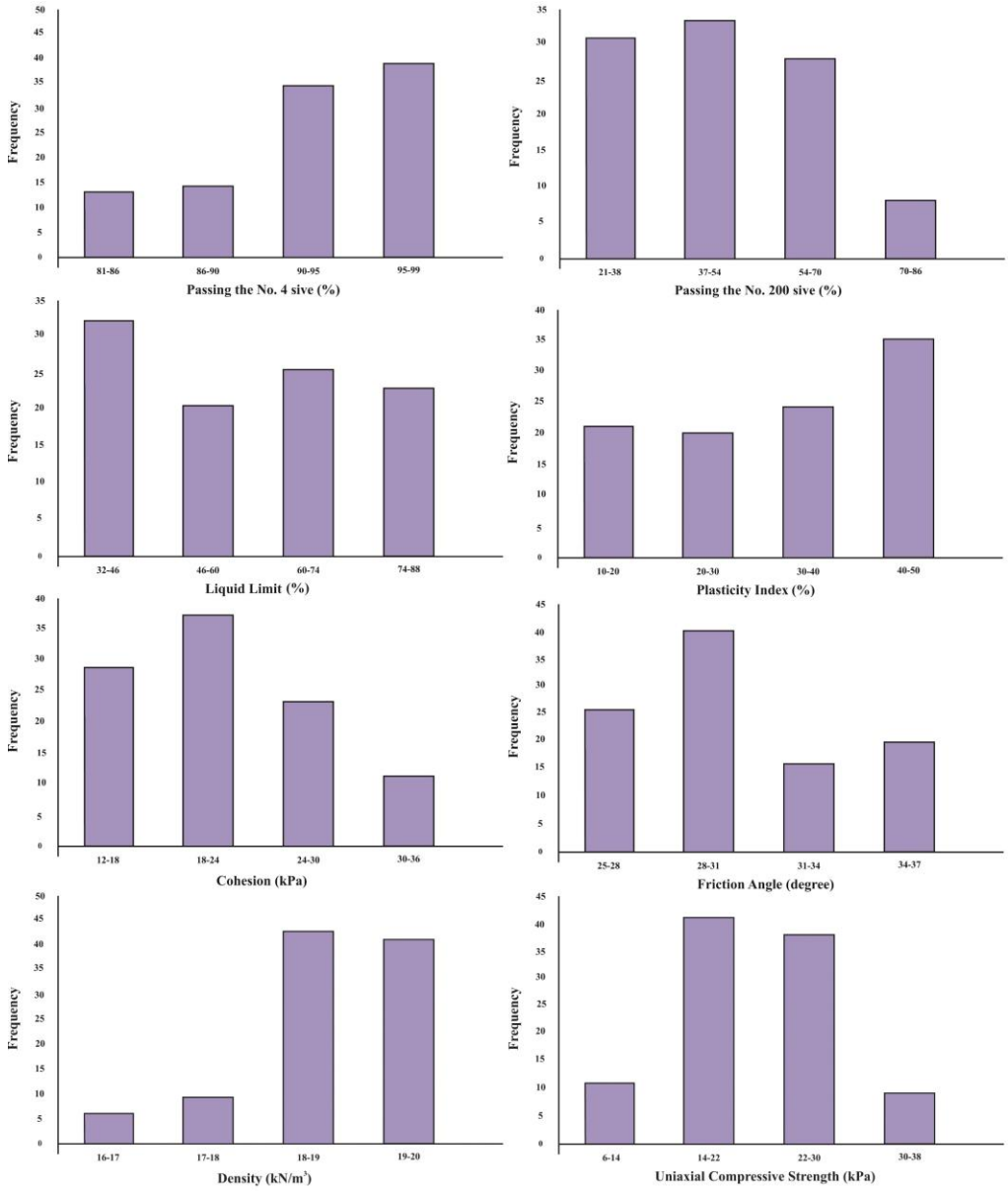

Fig. 2 Histogram of input variable variations

the initial data set to create the correlation matrix for this purpose. Pearson's correlation coefficients between C and φ, which are the dependent variables, and the other selected soil properties, which are the independent variables, have been examined in analysis which represents the Pearson coefficients. According to the Pearson correlation, the input variables are statistically in confidence level up to 93.57%.

2.3 Multilayer perceptron network principles

In the present study, multilayer perceptron (MLP), a type of Artificial Neural Network (ANN) techniques that has been used to estimate the shear strength parameters. MLP basically consists of multiple layers of nodes or neurons operated as a feed-forward neural network (FNN) which means that there are no feedback loops between the input and output nodes. Each neuron in an MLP uses an activation function to produce an output after performing a weighted sum of the inputs in the input layer and passing it through one or more hidden layers. Once the final output layer, which produces the network's output, is reached, the output of each hidden layer is fed as input to the next layer. An MLP's hidden layers make it possible for the network to learn complicated non-linear relationships between the input and output data, making it an effective tool for classification and regression (Abunama *et al*. 2019). Backpropagation, a supervised learning algorithm that adjusts the network's parameters based on the error between the predicted output and the true output, is typically used to train the MLP's biases and weights. Generally, MLP can be tailored to specific applications with a variety of architectures. However, time series forecasting and other tasks that require sequential data, such as recurrent neural networks (RNNs) or other types of networks, may benefit

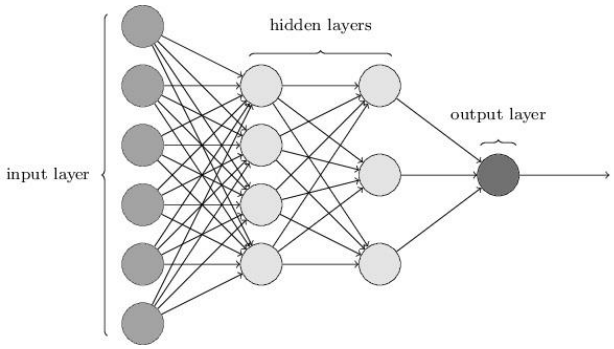

Fig. 3 A MLP neural network architecture (Hearty 2016)

more from their use (Weerakody *et al*. 2021). MLP is the most well-known kind of neural network utilized for regulated prediction. Network reaction routes of this kind always feed-forward and allow the signal to only change one route from input to output.

Fig. 3 is presented an MLP neural network architecture that concluded three layers of neurons. Each layers have been specific duty which can be briefed as (Bahnsen and Gonzalez 2011):

- Input layer: provide the variables that are entered in calculations,
- Hidden layer(s): the middle layers that are responsible to investigate, and assessment on input data,
- Output layer: this layer is export the results of the analysis.

Data is presented to the network at the input layer is consist of main geotechnical indexes that provided in pervious section. In fact, the data come from a variety of sources to the input layer. As a result, the number of input data sources determined the number of neurons in the input layer. To determine the degree of influence that variables have on dependent parameters, this study looked at various combinations of independent variables that were used as inputs to MLP models. To consider the base statically combination was providing in Table 3, the input data such as UCS, LL, PI, γ, percentage of fine-grains (pass #200), and sand (pass #4) was normalized by Pearson's coefficient. Fig. 4 is providing the Pearson's coefficient estimated for each input data were used to correlate the information.

A Pearson's coefficient of one indicates a perfect positive correlation, which indicates that when one variable rises, so does the other. This coefficient is a statistical measure that tells how much of a linear connection there is between two variables. The number "r" stands for it, and its values range from -1 to 1. A perfect negative correlation with a coefficient of -1 indicates that one variable increase while the other decreases. There is no correlation between the variables if the coefficient is 0. By dividing the covariance of the two variables by the product of their standard deviations, Pearson's coefficient can be calculated (Sedgwick 2012). Pearson's coefficient is calculated as follows

$$r = \frac{n\sum xy - \sum x \sum y}{\text{sqrt}\left[\{n\sum x^2 - (\sum x)^2\} \times \{n\sum y^2 - (\sum y)^2\}\right]} \quad (1)$$

where n is the number of observations, x and y are the two variables, Σxy is the sum of the products of x and y, Σx and Σy are the sums of x and y respectively, and Σx^2 and Σy^2 are the sums of the squares of x and y respectively. Pearson's coefficient is frequently used to examine the relationship between two variables which is used to provide a vision for the scatter ability for variables.

To serve as a collection of feature detectors, hidden layer(s) are utilized. The optimal number of hidden layers between the input and output layers as well as the optimal number of neurons in each layer is required for the construction of network architecture in MLP algorithms. Due to the absence of a unified theory for optimal architecture, this is one of the most important and challenging tasks (Kiranyaz *et al*. 2021). Trial and error are frequently used to determine the number of hidden layers and their neurons (Ibnu Choldun *et al*. 2020). An appropriate response to the input is generated using the extended output layer. An MLP is composed of one or more hidden layers of artificial neurons, each of which applies an activation function to its input. There are several commonly used activation functions in MLP which included the Sigmoid function, Hyperbolic tangent (tanh) function, Rectified Linear Unit (ReLU) function, Leaky ReLU function, and Softmax function (Liew *et al*. 2016). The sigmoid function maps any real value to the range (0,1), which makes it useful for classification problems. The function is defined as (Sharma *et al*. 2017)

$$\sigma(x) = \frac{1}{1+\exp(-x)} \quad (2)$$

Hyperbolic tangent function maps any real value to the range (-1,1), which makes it useful for classification problems where outputs can be negative or positive. The function is defined as (Szandała 2021)

$$\tanh(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)} \quad (3)$$

The ReLU function maps any negative value to zero, and any positive value to itself. It is commonly used in deep learning networks and has been shown to perform well in practice. The function is defined as ReLU(x) = max(0, x). Also, the Leaky ReLU function is similar to ReLU, but allows small negative values to be output (Leaky ReLU(x) = max(αx, x), where α is a small constant typically set to 0.01). The softmax function is commonly used as the output activation function in classification problems with multiple classes. It maps a vector of real values to a probability distribution over the classes.

$$\text{Softmax}(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_i)} \quad (4)$$

where i is the index of the current class, and j iterates over all classes. Presented study was used mentioned type of activation functions to respond the accurate prediction modelling which is included Sigmoid, Hyperbolic, ReLU and Softmax functions. Each model was run individually, and results were compared.

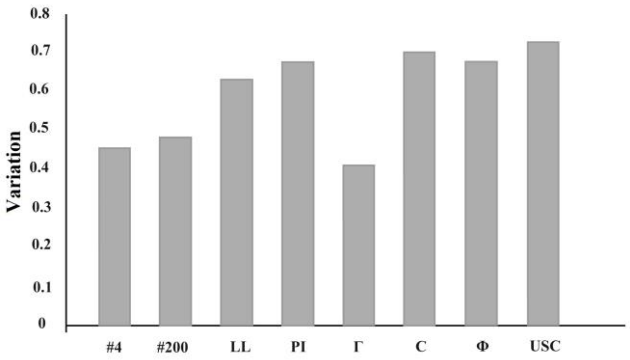

Fig. 4 Pearson's coefficient variation for each input data

For the purpose of training MLP networks, the backpropagation is widely utilized. The MLP is a type of artificial neural network with multiple layers of interconnected nodes. Each node is just a simple computational unit that uses an activation function to calculate a weighted sum of its inputs. Backpropagation reduces the difference between the network's output and the desired output by iteratively adjusting the weights of the connections between the MLP's nodes. A loss function that measures the network's prediction error is used to measure this difference. The backpropagation algorithm works by adjusting the weights of the connections based on the calculated error gradient as the error moves backwards through the network, from the output layer to the input layer. Calculus' chain rule is used to calculate the loss function's gradient with respect to each network weight, and an optimization technique like gradient descent is used to update the weights (Valizadeh 2021). The backpropagation algorithm registers the error signal Ep, which is a proportion of the network's exhibition for one handling component in the output layer, utilizing the accompanying equations (Khanlari *et al*. 2012)

$$Ep=\frac{1}{2}\sum(y_{ij}-o_{ij})^2 \tag{5}$$

$$E = \sum Ep \tag{6}$$

where y_{ij} is the ideal backpropagation output for j^{th} part of the output design for design i, and o_{ij} is the genuine backpropagation output for j^{th} processing component. The total error for the network is given by the Eq. (6). The new weights are assessed by utilizing the adjusted delta rule as (Diamantopoulou 2005)

$$w'_{ji}=w_{ij}+\Delta w_{ij} \tag{7}$$

$$\Delta w_{ij}= - \eta \frac{\partial E}{\partial w_{ij}} \tag{8}$$

where Δw_{ji} represents the incremental weight change and η is the learning rate that controls the update step size. To carry out the models of MLP to predict the shear strength parameters, the experimented data have been separated into training and testing datasets, randomly. The training set concludes 70% of the main database (100 different records for soil samples) and the testing set contains 30% of remaining database. In such circumstances, the training set contains 70 sample data, and testing is willing to be 30 samples. The training set was used to learn the model and verified by the testing set to calculate the predictive model performance and capability. The MLP models were implemented in Python high-level programming language.

2.4 Multivariate regression principles

Modeling the relationship between multiple independent variables (also known as predictors or features) and a dependent variable (also known as the response or target variable) is done with the statistical analysis technique known as multivariate regression. The objective of multivariate regression is to construct a mathematical equation that explains the connection between the independent and dependent variables. The values of the independent variables can then be used to predict the dependent variable using the equation (Mokkadem *et al*. 2008).

Both linear and nonlinear regressions were applied in this study in multivariate regression analysis. The results indicated that the ability of linear regression in the prediction of shear strength parameters is better. The multivariate regression links one dependent variable Y to k independent variables or predictors X_i (i= 1, …, k). The obtained equation can be applied for the prediction of Y as a linear combination of the predictors, namely

$$Y=a_0+a_1X_1+a_2X_2+....+a_kX_k \tag{9}$$

where Y is an estimate and the ais are considered as the regression coefficients. On the developmental sample of size n, the coefficients ais are chosen such that the sum of the squares of the estimation error is minimized

$$\text{Mine}(\underline{a}), \quad \text{where} \quad \text{mine}(\underline{a})=\sum_{j=1}^{n}[y_i-\hat{Y}(\overline{a})]^2 \tag{10}$$

where $\underline{a}=[a_0a_1a_2...a_k]^T$, The matricidal form of the coefficients can be solved using the least squares approach by

$$\underline{a}=(.\underline{\underline{X}}'\underline{\underline{X}}).\underline{\underline{X}}'\underline{Y} \tag{11}$$

where $\underline{a}$ is a vector containing the estimated coefficients of length N+1, and N is the number of predictors (X_i; i= 1;…; N). The $\underline{\underline{X}}'\underline{\underline{X}}$ matrix includes the sums of squares and cross products matrix and $y=[y_0y_1...y_n]^T$. The (j, k) element of the matrix is $\sum_{i=1}^{n}X_{ji}X_{ik}$, i= 1,…, N for a sample of size N.

2.5 Models implementation and verification

Confusion matrix was used to validate the testing and training data regarding prediction performance and capability. A confusion matrix is a table that is frequently used to evaluate a machine learning model's performance. It is a comparison of the model's predictions to the actual outcomes (Zhu *et al*. 2010). The confusion matrix typically consists of a two-by-two table that displays the number of predictions made by the model for true positive (TP), true negative (TN), false positive (FP), and false negative (FN) which can be summarized as well as Fig. 5 (Chicco and Jurman 2020):

- TP: The number of instances in which the model correctly predicted the positive class,
- TN: The number of instances in which model correctly predicted the negative class,
- FP: The number of times the positive class was incorrectly predicted by the model,
- FN: the number of times the negative class was incorrectly predicted by the model.

Accuracy, precision, recall, and the F1-score are just a few of the performance metrics that are frequently calculated using the confusion matrix. Insights into the model's overall performance can be gained from these metrics, which can also assist in locating areas in need of improvement (Chicco and Jurman 2020).

The exhibitions of the models created in this study have been surveyed utilizing different standard statistical execution assessment measures. The statistical measures considered have been coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), and root mean square error (RMSE). The four rules are determined by the accompanying equations.

Coefficient of determination or R-squared (R^2) is a number between 0 and 1, with 0 denoting that the model does not explain any of the data's variability and 1 denoting that the model does explain all of the data's variability. The proportion of the dependent variable's variance that is explained by the model's independent variables is known as R-squared. More specifically, it refers to the ratio of the total variance to the variance that was explained. The R-squared formula is as $R^2 = 1 - (SS_{res} / SS_{tot})$; where SS_{res} is the total sum of squares (the differences between the actual values and the mean of the dependent variable) and SS_{tot} is the sum of squares (the differences between the predicted values and the actual values). The range of R^2 values is from 0 to 1, with higher values indicating a better model-data fit. Having said that, it is essential to keep in mind that a high R^2 does not necessarily imply that the model is a good fit or that the independent variable(s) are causing the observed variation in the dependent variable. Instead, it could indicate the opposite.

As a result, R^2 should be used in conjunction with other measures and the data should be carefully interpreted (Rights and Sterba 2019). MAE is a metric used to evaluate the performance of a regression model. It measures the average magnitude of the errors between the predicted and actual values of the target variable. MAE is calculated as the average of the absolute differences between the

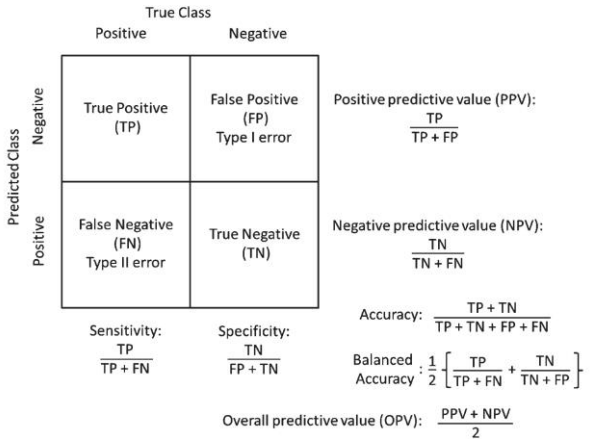

Fig. 5 A confusion table (Hahn *et al*. 2012)

predicted and actual values ($MAE = (1/n) * \sum |y - \hat{y}|$). In this equation n is the number of observations, y is the actual value of the target variable, and $\hat{y}$ is the predicted value of the target variable (Hodson 2022). MAE is a useful metric because it shows how much the model is off in its predictions on average. A model's performance is better if its MAE is lower, while its performance is worse if it is higher. MAE, in contrast to other metrics like MSE, gives equal weight to all errors, no matter how big they are. In situations where big mistakes are especially bad, this can be helpful (Chicco *et al*. 2021, Mao *et al*. 2023).

MSE is a commonly used metric to evaluate the performance of a regression model. It measures the average of the squared differences between the predicted and actual values of the target variable. The MSE gives a measure of the average magnitude of the error made by the model ($MSE = (1/n)\times\sum(y - \hat{y})^2$). In this equation n is the number of observations, y is the actual value of the target variable, and $\hat{y}$ is the predicted value of the target variable. The MSE has the advantage of giving a higher weight to larger errors since the errors are squared before being averaged. This means that the model is penalized more for larger errors, making it more sensitive to outliers (Chicco *et al*. 2021).

RMSE is a commonly used metric to evaluate the performance of a regression model. It measures the square root of the average of the squared differences between the predicted and actual values of the target variable. The RMSE is often used as an alternative to the MSE, which has the same advantages and disadvantages as the RMSE ($RMSE = sqrt\{(1/n)\times\sum(y - \hat{y})^2\}$). In this equation n is the number of observations, y is the actual value of the target variable, and $\hat{y}$ is the predicted value of the target variable. Like MSE, the RMSE gives a measure of the average magnitude of the error made by the model. However, since the RMSE is the square root of the MSE, it has the advantage of having the same unit as the original data. This makes it easier to interpret the results (Hodson 2022).

3. Results and discussion

Presented study used several MLP predictive model as well as multivariate regression analysis which is used for

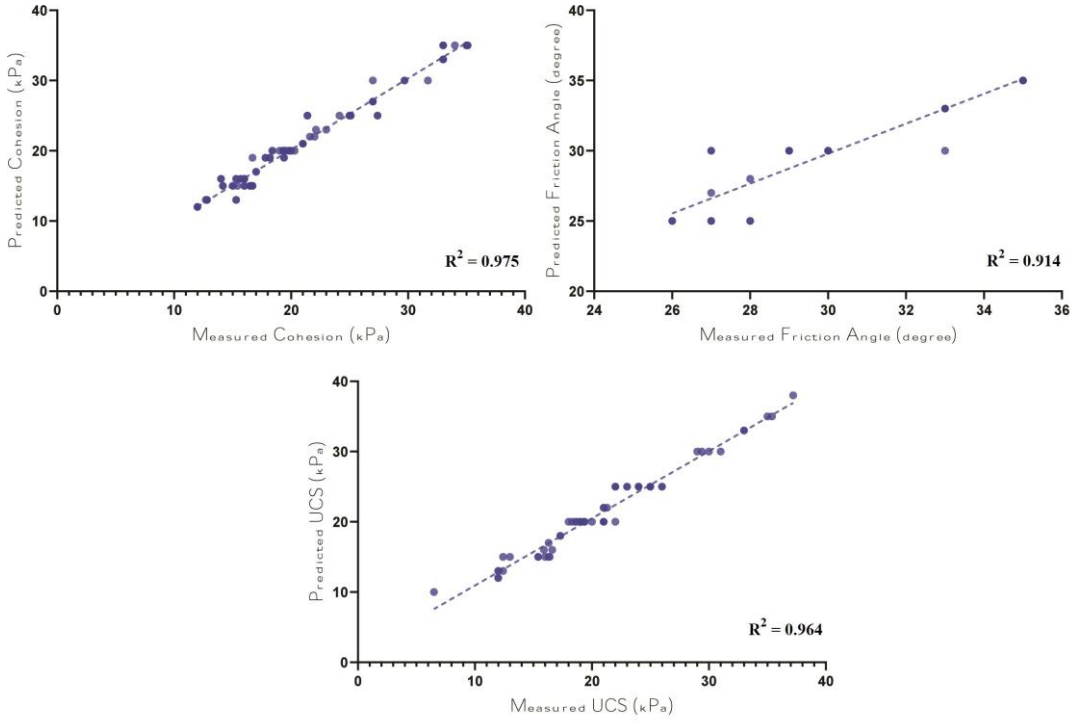

Fig. 6 Correlation diagram for the measured and predicted values in training dataset

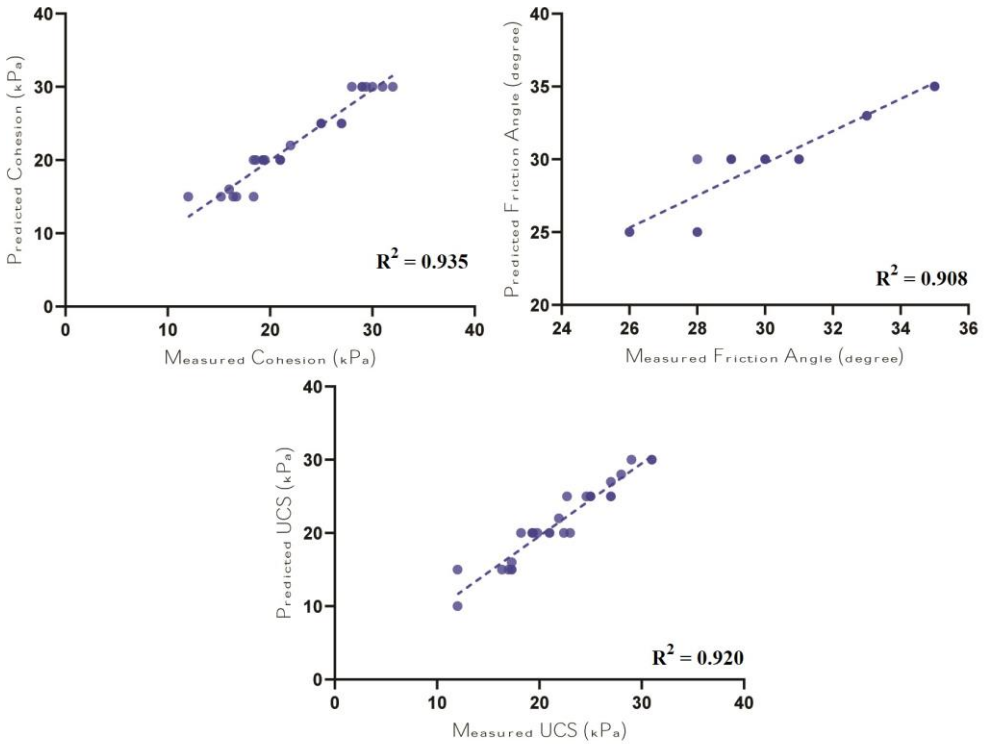

Fig. 7 Correlation diagram for the measured and predicted values in testing dataset

prediction of soil shear strength parameters such as friction, cohesion and UCS. The friction angle, cohesion, and UCS values are predicted by models directly based on input parameters which are compared with estimated values. Figs. 6 and 7 are provide the correlation diagram for testing and training datasets for friction angle, cohesion, and UCS which are estimated and predictive by experimental and predictive models, respectively. The estimated R^2 for friction angle, cohesion, and UCS are 0.914, 0.975, and 0.964 in the training dataset.

Table 4 Estimated performance metrics for various MLP models

Models	Parameter	Assessment performance metrics			Accuracy
		Precision	Recall	F1-score	
MLPSig	c (kPa)	0.935	0.903	0.920	0.925
	ϕ (o)	0.935	0.925	0.925	
	UCS (kPa)	0.925	0.935	0.935	
MLP_{Hyp}	c (kPa)	0.910	0.910	0.920	0.910
	ϕ (o)	0.910	0.920	0.920	
	UCS (kPa)	0.910	0.910	0.910	
MLP_{Relu}	c (kPa)	0.930	0.930	0.930	0.927
	ϕ (o)	0.927	0.927	0.930	
	UCS (kPa)	0.927	0.927	0.930	
MLP_{Soft}	c (kPa)	0.933	0.935	0.933	0.930
	ϕ (o)	0.933	0.935	0.933	
	UCS (kPa)	0.933	0.935	0.935	

Note: MLP_{Sig} is MLP with Sigmoid activation function, MLP_{Hyp} is MLP with Hyperbolic activation function, MLP_{Relu} is MLP with ReLU activation function, MLP_{Soft} is MLP with Softmax activation function

Table 5 Statistical errors estimation for various MLP models

Models	Training set			Testing set		
	MAE	MSE	RMSE	MAE	MSE	RMSE
MLP_{Sig}	2. 0231	2.0131	2.0659	2.2460	2.2449	2.2030
MLP_{Hyp}	2.1492	2.0865	2.0770	2.2554	2.2853	2.2921
MLP_{Relu}	2.1795	2.1545	2.1434	2.2517	2.2867	2.2804
MLP_{Soft}	2.0763	2.1208	2.0536	2.2833	2.2731	2.2779

The higher rate for R^2 indicates that the model has a considerable agreement with experimented values which shows the performance of predictive models.

As evaluated confusion matrix that leads to estimate the performance metrics (accuracy, precision, recall, and the F1-score) which illustrated in Table 4, it can be stated that the models are operated with high performance. According to this table, the estimated accuracy for various type of MLP models is illustrated as 0.925, 0.910, 0.927, and 0.930 which presented the Sigmoid and Softmax activation functions higher performance rate. Also, estimated precision for models is up to 0.935.

Table 5 present statistical error metrics for various MLR models implemented on output results such as friction angle, cohesion, and UCS. The ability of these indexes estimates is enhanced when the number of input variables in the regression models is increased, as shown in this table. Figs. 8 to 10 provide the estimated error index variations for each output result on the testing dataset used to model verification. According to the estimated result, it can be stated that the models were operated with a low error rate in testing and training levels which demonstrates the high-performance of the models. Referring to this table, the training model was learned under the 2.0231 (MAE) error rate and validated on 2.0131 (MSE), 2.2030 (RMSE) error rates which belong to the Sigmoid activation function. This demonstrates a significant and strong correlation between input and output information. The following is the MLR model equation for calculating friction angle (ϕ), cohesion (c), and UCS:

c = 0.02765 – 0.0139(#4) + 0.0462(#200) + 0.0695(PI) + 0.0241(UCS')

ϕ = 32.90 + 0.078(#4) − 0.00157(#200) – 0.0842(PI) + 0.0633(UCS')

UCS = 0.0203 + 0.0794(#4) – 0.0127(#200) – 0.00365(PI) + 0.0482(c') + 0.0119(ϕ')

where UCS', c' and ϕ' are the measured values in experiments which marked in the relationships.

Geotechnical engineers can apply the findings of this study to enhance the accuracy and reliability of soil strength predictions in real-world projects. By utilizing the multivariate regression and multilayer perceptron (MLP) models developed in this study, engineers can achieve more precise estimates of critical soil strength parameters such as friction angle (ϕ), cohesion (c), and uniaxial compressive strength (UCS). The models were validated using data from 100 soil specimens from the Tabriz region in Iran, showing high accuracy and precision rates (around 93%). This level of accuracy can significantly improve the design and stability analysis of foundations, retaining walls, slopes, and other geotechnical structures. By integrating these advanced predictive tools into their workflows, engineers can reduce the risk of structural failures, optimize material usage, and ensure more efficient and safer project outcomes.

The MLP was selected for this study because of its proven effectiveness in capturing non-linear relationships in data, which is crucial for predicting soil shear strength parameters. While MLP is a relatively basic neural network and machine learning model, it offers significant

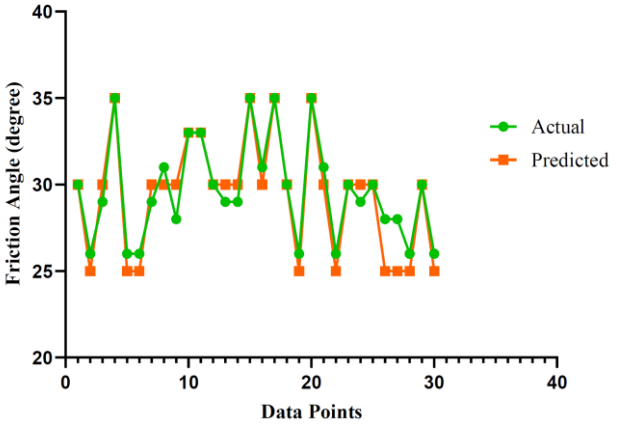

Fig. 8 Error variation in testing data set for friction angle

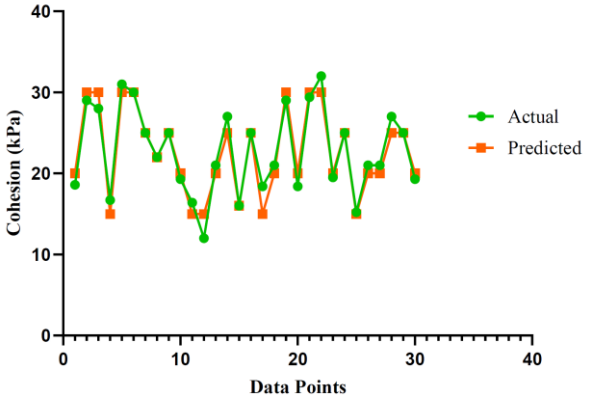

Fig. 9 Error variation in testing data set for cohesion

advantages, including simplicity, efficiency, and ease of implementation. These qualities make it a reliable choice for working with the dataset used in this research.

To ensure high accuracy, we did not rely solely on the standard MLP model. Instead, we made specific modifications to enhance its performance. These adjustments included fine-tuning the network's architecture, optimizing key hyperparameters, and applying advanced training techniques. As a result, we were able to achieve an accuracy of approximately 93%, demonstrating that with the right modifications, even a basic model like MLP can perform exceptionally well. Although more complex models, such as deep neural networks or ensemble methods, could potentially offer further improvements, the modified MLP provided a strong balance between predictive accuracy and computational efficiency. This makes it particularly well-suited for the type of geotechnical data used in this study, where maintaining a high level of precision is critical, but computational resources may be limited.

The prospects for applying these predictive models in actual engineering projects are promising, especially given their demonstrated accuracy in predicting soil shear strength parameters. The study's results, which show a high level of accuracy and precision using models like the MLP, suggest that these models can significantly enhance the reliability of geotechnical designs. While the study itself focused on data from the Tabriz region, further validation through specific

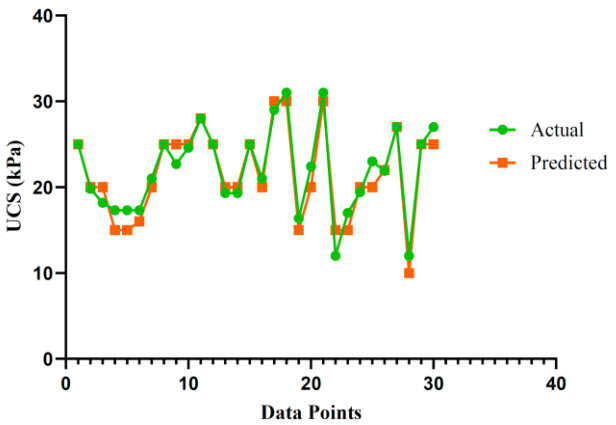

Fig. 10 Error variation in testing data set for UCS

case studies or experiments in diverse geographical and geological settings would strengthen confidence in these models' practical utility. Such validations could involve applying the models to real-world projects, like foundation design or slope stability analysis, and comparing their predictions with observed outcomes to confirm their effectiveness and reliability in various engineering scenarios.

4. Conclusions

The ability of multivariate linear regression and artificial neural networks to predict soil shear strength parameters (C, ϕ and UCS) has been the subject of this investigation. In this regard, 100 soil samples were taken from Tabriz region, northwest of Iran to calculate the soil strength parameters. The measured data is obtained from various geotechnical tests that performed on taken specimens which results was used in a main database. This database was randomly divided into the training dataset (70% of the main database) and the testing dataset (30% remain of the database). These datasets were used to learn and validate the predictive models which implemented in Python high-level programming language. The UCS, LL, PI, γ, and percentage of fine-grains (pass #200) and sand (pass #4) are used as input parameters of analysis and shear strength parameters predictions. The ϕ, c, and UCS are considered index strength properties that were exported as output. Input data was statistically normalized and entered in the MLP algorithm with various activation functions including Sigmoid, Hyperbolic, ReLU, and Softmax functions. A confusion matrix, as well as statistical error metrics, were used to control the predictive model performance and capability which included MAE, MSE, and RMSE. The R-square was used to determine the correlation between the collected and predicted information in the test and training datasets. According to the results, MLP models' accuracy was estimated at 0.925, 0.910, 0.927, and 0.930 for different activation functions which operated under 2.0231 (MAE), 2.0131 (MSE), and 2.2030 (RMSE) error rates. Regarding the accuracy and error variation, it can be stated that the predictive models are conducted high-accurate predictions

with low errors. Also, R^2 estimated for predictions process are 0.914, 0.975, and 0.964 in training dataset for friction angle, cohesion, and UCS were considerable.

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