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Advanced prediction of soil shear strength parameters using index properties and artificial neural network approach

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Abstract

This study embarks on developing predictive models for soil shear strength parameters, cohesion (c) and angle of internal friction (ϕ), in Bishoftu town, employing Artificial Neural Networks (ANN). It aims at offering a cost-effective and time-saving alternative to traditional, often expensive, and labor-intensive laboratory methods. The research utilizes soil index properties such as Sand %, Fines %, Liquid Limit, Plastic Limit, and Plasticity Index to construct separate ANN models for c and ϕ. These models use a multi-layer perceptron network with feed-forward back propagation, varying the number of hidden layers to optimize performance. The study's dataset comprises 316 soil test results, encompassing both primary and secondary data, conforming to ASTM Standards. Soil cohesion and internal friction angle were determined using the direct shear box method. The models demonstrated remarkable success in predicting shear strength parameters, evidenced by correlation values of approximately 0.99 for cohesion and 0.98 for internal friction angle, surpassing the capabilities of existing empirical methods. Further examination of the models included comparison with existing correlation techniques and cross-validation using primary soil test data. This validation process confirmed the ANN method's superior accuracy and fit for predicting shear strength parameters over selected empirical methods. This research substantiates the efficiency of ANN in geotechnical engineering, particularly for areas with limited resources for extensive soil testing. It establishes ANN as a powerful, efficient tool for estimating soil shear strength parameters, with significant implications for future planning, design, and construction projects in similar environments.

Keywords: ANN; Shear Strength; Cohesion; Friction Angle; Prediction; Index Properties.

1. Introduction

In this study, we delve into the critical importance of soil shear strength parameters, cohesion, and internal friction angle, for urban development projects. These parameters are indispensable for foundation analysis and the stability of various structures. Traditional methods to determine these parameters, such as direct shear and triaxial compression tests, are often costly and labor-intensive [9, 10]. They also face challenges in acquiring accurate soil samples, particularly in developing countries. This has led to a reliance on empirical correlations in geotechnical practice, which, despite their utility, have limitations in predicting shear strength for diverse soil mixtures [17, 55].

The advent of Artificial Neural Networks (ANN) offers a promising alternative. With its capacity to model complex problems, ANN is transforming various fields, including engineering [1, 6]. This research proposes the use of ANN to predict shear strength parameters from soil index properties, a significant shift from conventional methodologies [29, 30]. The aim is to provide a more efficient, cost-effective solution to traditional soil testing methods. By developing a

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model that correlates soil index properties with shear strength parameters, this study seeks to minimize the time, effort, and expense typically involved in geotechnical engineering practices [19, 20].

The introduction of ANN into this field is not just a technical advancement; it represents a paradigm shift in how soil mechanics are approached and understood [11, 27]. This study's innovative approach promises to address the practical challenges of soil testing while enhancing the accuracy and efficiency of geotechnical design and analysis [21, 24]. The research stands at the intersection of traditional geotechnical methods and modern computational techniques, potentially revolutionizing the way soil shear strength is estimated and applied in real-world scenarios.

This study not only contributes to the existing body of knowledge in geotechnical engineering but also opens new avenues for research and application. The findings could have far-reaching implications for the future of urban development, particularly in regions where resources for extensive soil testing are limited [26, 28]. By bridging the gap between conventional practices and advanced computational methods, this research aims to provide a robust, reliable, and accessible tool for engineers and practitioners in the field.

2. Material and Methods

In this study, the choice of Bishoftu, Ethiopia, as the study area is significant due to its unique geotechnical characteristics. Bishoftu, situated in the Oromia Region, is renowned for its distinct geological features, including a variety of soil types, notably Vertisols, which are key to this study [9, 29]. The region's geographical setting in the Great Rift Valley, coupled with its varied topography and climate, presents a unique opportunity to study the soil's behaviour under different conditions [10, 17]. The town's proximity to Addis Ababa, diverse land use, and presence of crater lakes add to its geotechnical interest, making it an ideal location for investigating soil shear strength parameters using advanced techniques like Artificial Neural Networks (ANN) [1, 6]. This setting provides a comprehensive backdrop for exploring soil mechanics in a context that combines urban development pressures with natural geological complexity.

2.1. Study Area Description

Bishoftu, situated in Ethiopia's Oromia Region, is geographically positioned within the Great Rift Valley, about 47 kilometers southeast of the capital city, Addis Ababa. The town is elevated at approximately 1,920 meters above sea level. Known for its remarkable crater lakes and hot springs, Bishoftu's climate is generally moderate, which aids in sustaining diverse flora and fauna. The soil predominantly comprises Vertisols, characterized by high clay content, which leads to significant shrink-swell behavior [55]. This soil type, along with the town's geological setting, makes it a focal point for studying soil mechanics and behaviors under varying environmental conditions [54]. The demographic composition and historical aspects of Bishoftu also add layers to understanding its environmental and geotechnical dynamics.

2.2. Data Collection Methodology

In this study, 316 soil samples were collected from Bishoftu, Ethiopia, to develop an Artificial Neural Network (ANN) model [30]. The selection of sampling sites, as detailed in Table 1 and Figure 1, was strategic to encompass a broad range of soil types present in urban, industrial, and newly developed areas. The primary data collection followed ASTM D 2488 standards, focusing on comprehensive field identification and characterization of the soil [19, 20]. The sample locations included diverse sites such as Sunshine, Babogaya, and the Indomie Factory area, ensuring a representative cross-section of the town's geotechnical profile.

Table 1 Sample Location and Depth of Primary Data Soil Samples

Locations	Test pit number	Latitude	Longitude	Sample depth(m)
Sunshine	Tp 1	8.734650	39.008535	1.5
Sunshine	Tp 2	8.73230	39.00991	1.5
Babugaya	Tp 3	8.7930	38.9909	1.5
Airforce	Tp 4	8.723886	38.992990	1.5
Ude/ Denkaka	Tp 5	8.681255	39.0345	1.5
Kurkura	Tp 6	8.7422873	38.9327956	1.5

Kurkura	Tp 7	8.7560845	38.9600119	1.5
Near Dukem	Tp 8	8.7774865	38.9327956	1.5
China sefer	Tp 9	8.72073	39.01019	1.5
Meda/Mesalemiya	Tp 10	8.71691	39.01350	1.5
Ashewa sefer	Tp 11	8.70556	39.02229	1.5
Indomie factory	Tp 12	8.6937	39.0329	1.5
TVET	Tp 13	8.78728	38.99817	1.5
Adis Sefer	Tp 14	8.7508467	38.9634737	1.5
Adis sefer	Tp 15	8.758992	38.949442	1.5

Figure 1 Google locations of sampling test pits

Laboratory tests, crucial for data analysis, included grain size distribution and Atterberg limits, conducted according to the ASTM manual, as listed in Table 2. This methodical approach in data collection and testing was instrumental in obtaining a diverse and accurate dataset, essential for the effective training and validation of the ANN models.

Table 2 ASTM Manual of Standard Test Methods

Test Type	**ASTM Standard Manual**
Grain size distribution	D 4318-00
Atterberg limits	D 1140-14
Direct shear test	D3080-04
Field identification of soils	D 2488-00
Sample preserving and transporting	D 4220-95

In this study, the shear strength parameters of soil, specifically cohesion and internal friction angle, are the target output variables for the ANN models. The choice of appropriate input variables, closely correlated with these outputs, is crucial for achieving accurate predictions. Historical research indicates that soil index properties, such as grain size distribution and Atterberg limits, are commonly used and effective input parameters for predicting soil shear strength in both ANN and regression analysis contexts [9, 17, 29]. These properties have been demonstrated to have a strong correlation with the shear strength parameters [54, 55]. In this study, similar input parameters are utilized. To validate the relationship between inputs and outputs, scatter plots and least square regression methods are employed, providing a visual and analytical representation of the correlation.

2.3. ANN Modeling Procedure

The ANN Modeling Procedure was carried out using established methodologies in the past [1, 6]. The procedure began with data preprocessing, which involved integrating, cleaning, and reducing data for quality assurance. This phase was crucial in handling the large and diverse dataset. MATLAB R2018a was utilized as the tool for model development [19, 20]. The neural networks were modeled using custom scripts, allowing for greater flexibility in architecture and training methods. The model development phase included dividing data into training, validation, and testing sets, defining the neural network's architecture, and training it using the Levenberg-Marquardt algorithm [11, 27]. Cross-validation was conducted with primary soil data to assess the models' accuracy [21, 24]. The models' performance was evaluated using statistical measures like MSE and RMSE, and finally, the ANN model equations were derived, incorporating steps such as normalizing input variables, and calculating weighted sums.

3. Results and discussion

3.1. Laboratory Test Results

Soil samples were analyzed to determine their index properties and shear strength parameters. Three key tests - grain size analysis, Atterberg limits, and direct shear tests - were conducted on 15 primary data samples. The results, essential for further analysis, are summarized in Table 3, showcasing data such as the percentage of sand and fines, liquid limit (LL), plastic limit (PL), plasticity index (PI), cohesion (c), and angle of internal friction (ϕ) for each test pit.

Table 3 Summary of the Primary Data Soil Test Results

Test Pit No.	Grain size distribution		Atterberg limits			Shear strength parameters	
	% Sand	% Fine	LL	PL	PI	c	ϕ
TP 1	16.2	82.8	59.8	29.8	30	7	24
TP 2	5	94.1	83.4	36.2	47.2	21	18
TP 3	6	93.8	61.6	30.7	30.9	21	19
TP 4	4	95.5	89	35	54	15	19
TP 5	8	91.2	65.5	27	38.5	22	20
TP 6	13	86.6	57.2	33.4	23.8	10	28
TP 7	10.5	87.2	94.4	40.7	53.7	6	30
TP 8	4.6	94.4	90	37.8	52.2	23	19
TP 9	4	96	71	38	33	37	5
TP 10	7	93	72	35	37	35	4
TP 11	4	96	73	37	36	39	3
TP 12	6	94	75	37	38	38	3
TP 13	11	69	40.3	35.8	4.5	12	22
TP 14	20	56	42.4	35.2	7.2	14	22
TP 15	15	85	48.7	36.2	12.5	26	18

3.2. Secondary Data Analysis

The secondary data analysis, detailed in Table 4, revealed that the median and mean values of various soil properties were closely aligned, suggesting a near-normal distribution of the soil experimental data. This observation was further supported by the skewness values ranging from -0.835 to 1.785. Notably, cohesion values averaged 23.8 kPa, with a standard deviation of 7.6 kPa, spanning a range from 2 kPa to 51 kPa. Similarly, friction angles showed a mean of 14.25°, ranging from 2° to 24°.

Table 4 Descriptive Statistics of the Secondary Data Soil Test Results

Parameter	% Sand	%Fine	LL	PL	PI	c	ϕ
Mean	18.596	76.732	54.449	29.791	24.680	23.830	14.255
Standard error	0.635	0.716	0.943	0.578	0.667	0.438	0.239
Median	16.77	75.32	52	33	23	24	15
Standard deviation	11.024	12.424	16.372	10.029	11.579	7.604	4.153
Sample variance	121.529	154.374	268.065	100.587	134.080	57.834	17.251
Skewness	1.785	-0.835	1.194	-0.484	1.574	0.006	-0.008
Range	72.14	68.09	89.81	42	71.32	49	22
Minimum	1	30.91	29	8	3.2	2	2
Maximum	73.14	99	118.81	50	74.52	51	24
Count (N)	301	301	301	301	301	301	301

The correlation matrix in Table 5 indicated a strong correlation between liquid limit and plasticity index, while other variable pairs showed less significant correlations. This lack of strong correlations among most variables suggests that using regression analysis for model predictions could be less effective than Artificial Neural Networks (ANNs) for these parameters.

Table 5 Pearson's Correlation Matrix of the Variables

Soil Parameters	% Sand	% Fine	LL	PL	PI	c	ϕ
% Sand	1						
% Fine	-0.88483	1					
LL	-0.06347	0.207216	1				
PL	-0.01169	0.217839	0.715986	1			
PI	-0.07885	0.105383	0.796042	0.148216	1		
C	-0.04602	0.10268	-0.09233	0.142356	-0.25876	1	
ϕ	0.014105	0.285149	0.645335	0.670724	0.334024	-0.0767	1

3.3. Primary Data Analysis

The primary data analysis, outlined in Table 6, involved statistical evaluation of laboratory test results. Cohesion values varied between 6 kPa and 39 kPa, while friction angles ranged from 3° to 30°. The analysis provided detailed metrics such as mean, median, standard deviation, and range for various soil parameters, including sand percentage, fine percentage, liquid limit (LL), plastic limit (PL), plasticity index (PI), cohesion (c), and friction angle (ϕ). These statistics offer a comprehensive understanding of the soil properties under study.

Table 6 Descriptive Statistics of the Primary Data Set

Parameters	% Sand	%Fine	LL	PL	PI	c	ϕ
Mean	8.953	87.64	68.22	34.986	33.233	21.8	15.666
Standard error	1.317	2.918	4.355	0.907	4.091	2.900	2.375
Median	7	93	71	35.8	36	21	19
Standard deviation	5.101	11.304	16.868	3.515	15.846	11.232	9.201
Sample variance	26.029	127.785	284.544	12.355	251.099	126.171	84.666
Skewness	0.905	-2.017	-0.127	-0.901	-0.492	0.307	-0.267
Range	16	40	54.1	13.7	49.5	33	27
Minimum	4	56	40.3	27	4.5	6	3
Maximum	20	96	94.4	40.7	54	39	30
Count (N)	15	15	15	15	15	15	15

3.4. ANN Prediction Model

In the ANN Prediction Model section, extensive data analysis and neural network modeling were conducted. A total of 301 secondary data points were categorized for training, testing, and validation purposes, adhering to a 70-15-15% distribution. The study's primary focus was on developing models to predict soil cohesion and internal friction angle. Two specific models, Model 7 for cohesion and Model 12 for internal friction angle, were highlighted for their superior performance and reliability. These models underwent rigorous evaluation based on various metrics like the correlation coefficient, mean squared error, and root mean squared error.

The intricate network architecture and model characteristics, such as the number of neurons, layers, and learning methods, were comprehensively detailed in the relevant tables (Tables 7, 8, and 9) and visually represented through figures (Figures 2, 3, 4, and 5), which illustrated the neural network structures and regression plots. These models, especially Model 7 and 12, demonstrated high prediction accuracy, making them valuable tools for soil property analysis.

Table 7 Summary of the Developed Neural Network Models Characteristics

Parameters	Descriptions
Input parameters	Sand%, Fine%, LL, PL, and PI
Output parameters	c, ϕ
Number of hidden neurons	Trial and error (from 6 to 20)
Number of hidden layers	1
Learning method	Supervised learning
Network type	Feed forward Back propagation
Architecture	Multilayer Perceptron (MLP)
Data division	Random (dividerand)
Hidden layer activation function	Hyperbolic tangent Sigmoid function(tansig)
Output layer activation function	Linear function (purelin)
Training function	Levenberg-Marquardt (trainlm)
Performance function	MSE

Table 8 Prediction Models Developed for c

		Correlation Coefficient, R					
Model No.	Network	Training	Validation	Test	All	MSE	RMSE
1	5-6-1	0.74746	0.69639	0.72504	0.73455	26.02	5.1
2	5-7-1	0.95116	0.90815	0.68223	0.87421	8.48	2.91
3	5-8-1	0.75302	0.79148	0.6953	0.7427	25.02	5.001
4	5-9-1	0.96323	0.95851	0.88023	0.94954	3.99	1.99
5	5-9-1	0.95935	0.91906	0.87589	0.93422	11.39	3.37
6	5-10-1	0.95055	0.82408	0.82024	0.90464	22.01	4.69
7	**5-10-1**	**0.99929**	**0.99887**	**0.99725**	**0.99894**	**1.27**	**1.12**
8	5-10-1	0.94444	0.8826	0.8554	0.91624	10.83	3.29
9	5-10-1	0.95755	0.96581	0.82193	0.93477	3.13	1.76
10	5-11-1	0.93867	0.87302	0.84632	0.91207	12.58	3.54
11	5-11-1	0.96586	0.94359	0.94144	0.95697	6.73	2.59
12	5-12-1	0.996	0.98519	0.9752	0.99204	1.49	1.22
13	5-13-1	0.70719	0.45864	0.78273	0.65523	71.50	8.45
14	5-14-1	0.98559	0.92045	0.81711	0.9483	12.91	3.59
15	5-15-1	0.98405	0.95711	0.94925	0.97723	4.09	2.02
16	5-16-1	0.89291	0.82943	0.82372	0.87032	19.97	4.46
17	5-17-1	0.88486	0.9134	0.61214	0.85491	9.47	3.07
18	5-18-1	0.99209	0.93325	0.9297	0.97666	6.83	2.61
19	5-19-1	0.99609	0.97199	0.97262	0.99007	2.25	1.5
20	5-20-1	0.98204	0.85055	0.80104	0.92878	20.69	4.54

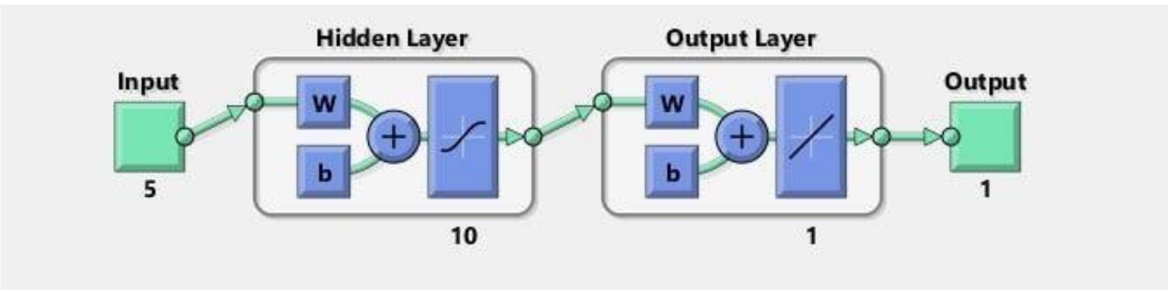

Figure 2 Neural Network Architecture Sample of the Model 7

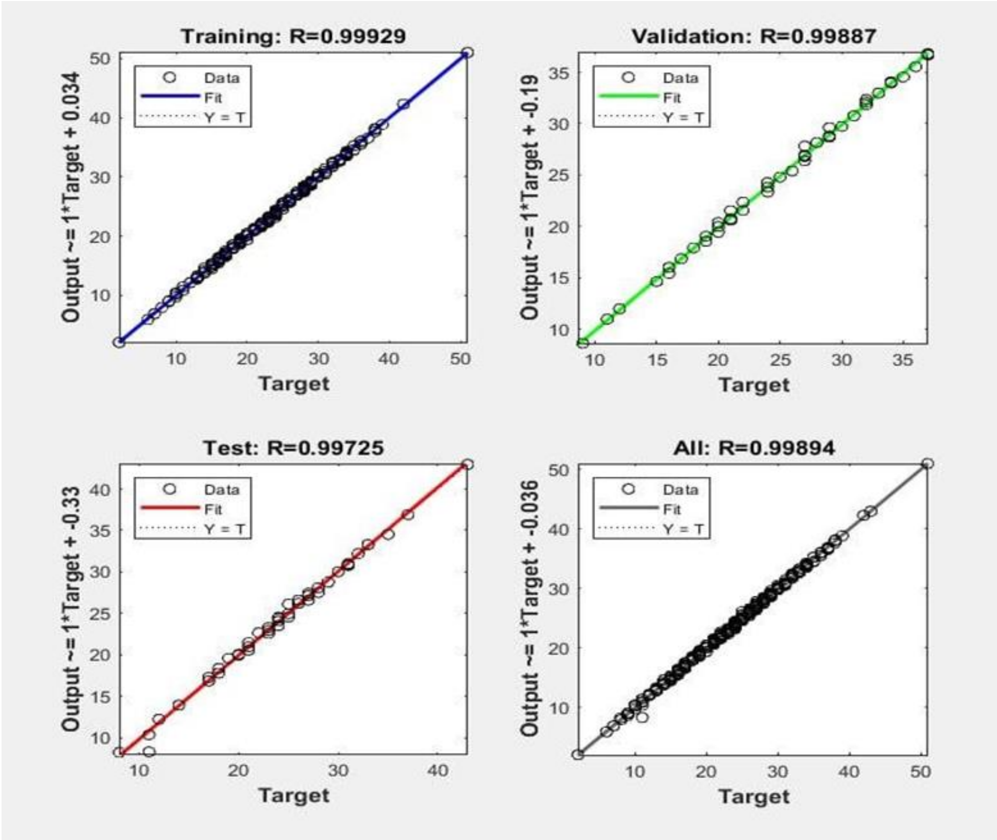

Figure 3 Regression Plot of Model 7

Model 7 achieved high R values (0.99929 for training, 0.99887 for validation, 0.99725 for testing, and 0.99894 overall) and low MSE and RMSE (1.27 and 1.12 respectively).

Table 9 Prediction Models Developed for ϕ

		Correlation Coefficient, R					
Model No.	**Network**	**Training**	**Validation**	**Test**	**All**	**MSE**	**RMSE**
1	5-6-1	0.85878	0.74239	0.82233	0.8379	7.05	2.65
2	5-7-1	0.97153	0.87693	0.90529	0.95109	3.34	1.82
3	5-8-1	0.97133	0.98091	0.94532	0.96917	7.04	2.65
4	5-9-1	0.92348	0.88956	0.91779	0.91841	3.63	1.90
5	5-9-1	0.95282	0.74342	0.75285	0.88068	10.93	3.30
6	5-10-1	0.86552	0.78924	0.87272	0.85309	17.55	4.18
7	5-10-1	0.99066	0.98297	0.97752	0.98728	5.76	2.4
8	5-10-1	0.9742	0.93777	0.92502	0.96188	2.30	1.51
9	5-10-1	0.98775	0.96981	0.89589	0.97243	1.86	1.36
10	5-11-1	0.98605	0.97526	0.97786	0.98311	7.57	2.75
11	5-11-1	0.99271	0.94491	0.98311	0.98258	2.28	1.50
12	**5-11-1**	**0.98904**	**0.96517**	**0.94741**	**0.97941**	**1.15**	**1.07**
13	5-12-1	0.95195	0.80187	0.88126	0.91078	9.09	3.01

14	5-12-1	0.877	0.84375	0.87557	0.87004	6.07	2.46
15	5-13-1	0.9751	0.89656	0.76492	0.92877	3.02	1.73
16	5-14-1	0.5587	0.42432	0.53689	0.50061	40.99	6.40
17	5-15-1	0.97206	0.71885	0.96158	0.93092	6.61	2.57
18	5-16-1	0.66084	0.357	0.74773	0.51804	56.90	7.54
19	5-17-1	0.9314	0.75582	0.88673	0.86934	12.89	3.59
20	5-18-1	0.93978	0.69117	0.94289	0.84762	37.53	6.12

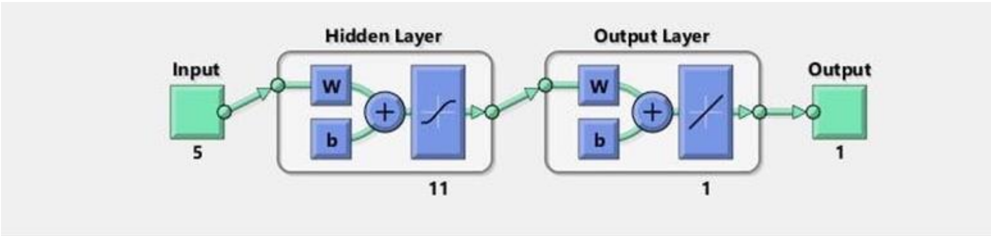

Figure 4 Neural Network Architecture Sample of the Model 12

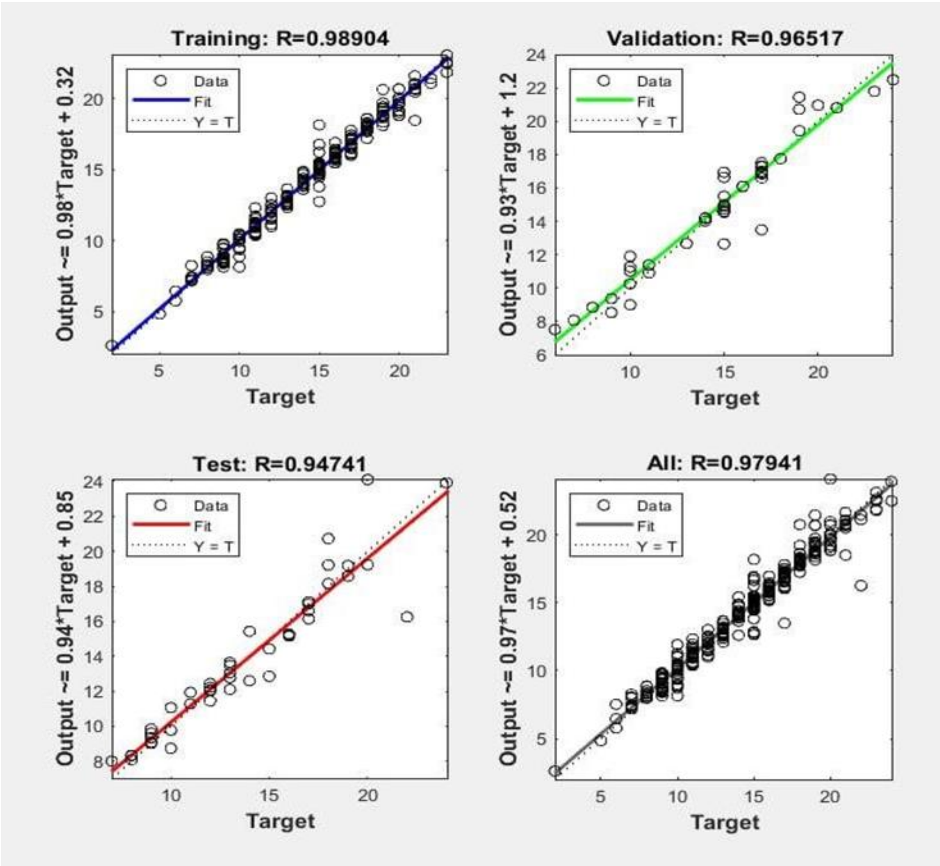

Figure 5 Regression plot of Model 12

Model 12 also showed impressive performance, with R values of 0.98904 for training, 0.96517 for validation, 0.94741 for testing, and 0.97941 overall, and MSE and RMSE values of 1.15 and 1.07 respectively.

3.5. Model Validation and Performance Evaluation

The cross-validation of the model for cohesion (c) prediction showed high accuracy, with an average difference of 1.8 kPa, an R value of 0.98, and an RMSE of 1.49. This is evident from the data in Table 10 and Figure 6.

Table 10 Experimental and Predicted Values of c for Primary Data Set

Experimental c (kPa)	Predicted c(kPa)	Difference (kPa)
7	5.8	-1.2
21	21.6	0.6
21	18.3	-2.7
15	19.2	4.2
22	21.8	-0.2
10	11.1	1.1
6	6.1	0.1
23	25	2
37	36.7	-0.3
35	34.9	-0.1
39	38.3	-0.7
38	37.7	-0.3
12	10.4	-1.6
14	15	1
26	25.9	-0.1
Average difference (kPa)		= 1.8

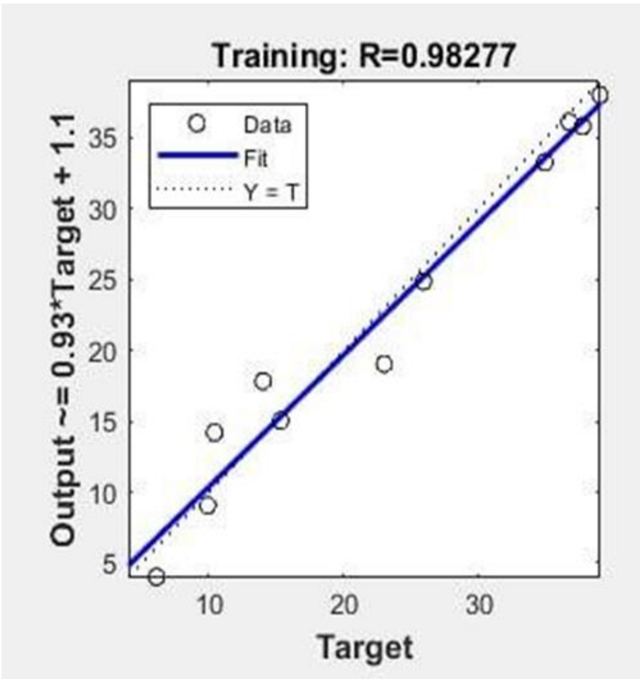

Figure 6 Regression Plot of Prediction of c Value for Primary Data Set

For internal friction angle (ϕ) prediction, the model also performed well, showing an average difference of 1.5°, an R value of 0.98, and an RMSE of 1.86. The maximum difference in ϕ prediction was 3.6°, indicating some instances of deviation, but overall, the model maintained high accuracy and reliability in predictions. These results are detailed in Table 11 and Figure 7.

Table 11 Experimental and Predicted Values of ϕ for Primary Data Set

Experimental ϕ (°)	Predictedϕ (°)	Difference ϕ (°)
24	24.6	0.6
18	15.5	-2.5
19	19.4	0.4
19	18.4	-0.6
20	20.1	0.1
28	24.4	-3.6
30	31.1	1.1
19	19.5	0.5
5	6.5	1.5
4	5	1
3	4.2	1.2
3	4.5	1.5
22	20.8	-1.2
22	21.8	-0.2
18	19.7	1.7
Average difference (°)		1.5

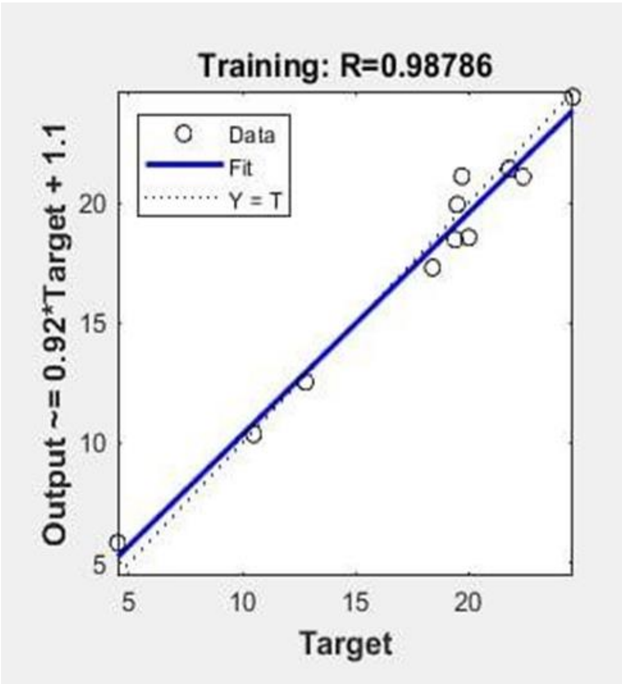

Figure 7 Regression Plot of Prediction of ϕ Value for Primary Data Set

The Artificial Neural Network (ANN) models for predicting cohesion (c) and internal friction angle (ϕ) displayed high accuracy. Model 7, designated for c prediction, achieved an impressive correlation coefficient (R value) of 0.99, both in testing and combined datasets, as illustrated in Figure 8. The error histogram (Figure 9) further supported the model's precision.

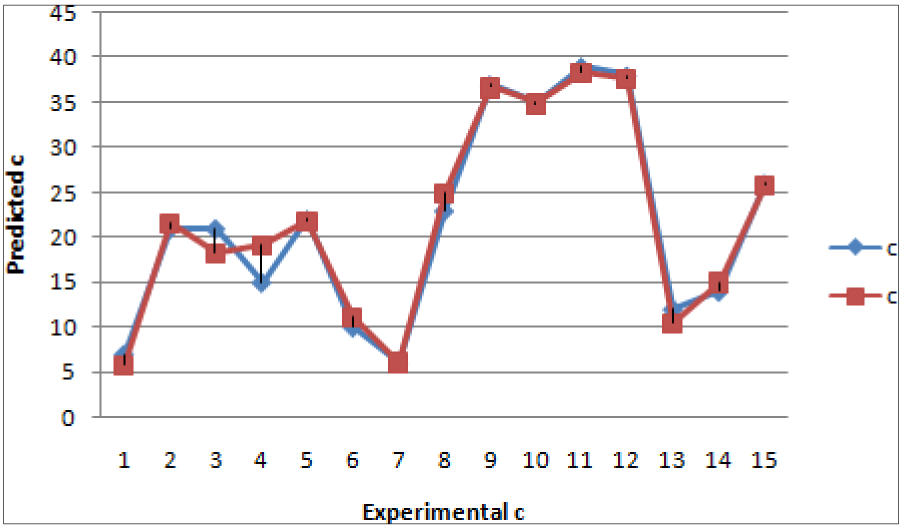

Figure 8 Comparison of Measured and Predicted c Value of Model 7

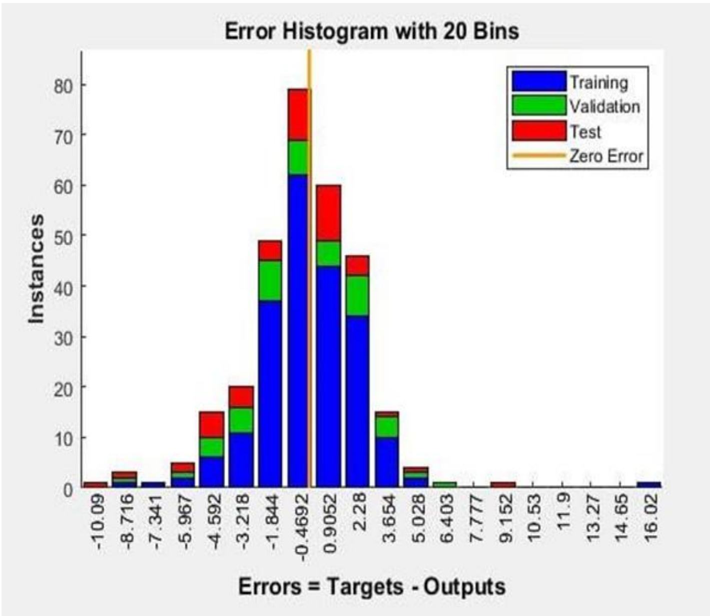

Figure 9 Error Histogram of Model 7 for Prediction of c

Similarly, Model 12, aimed at ϕ prediction, showed R values of 0.98 and 0.97, respectively, signifying strong correlation and accuracy, as depicted in Figure 10. The error distribution, observed in Figure 11, indicated minimal deviation between predicted and actual values.

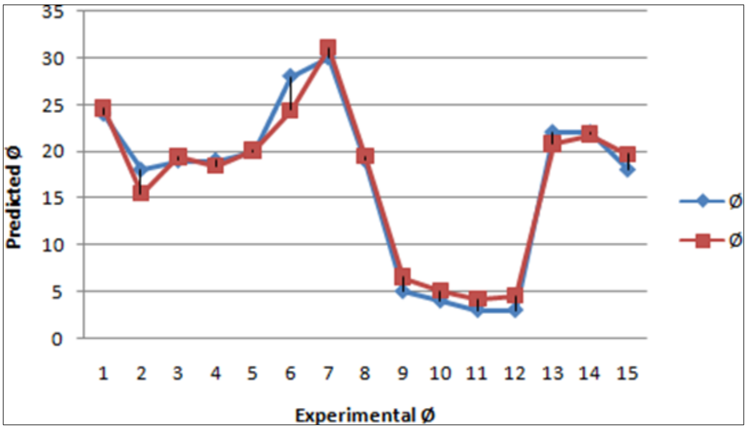

Figure 10 Comparison of measured and predicted ϕ value of model 12

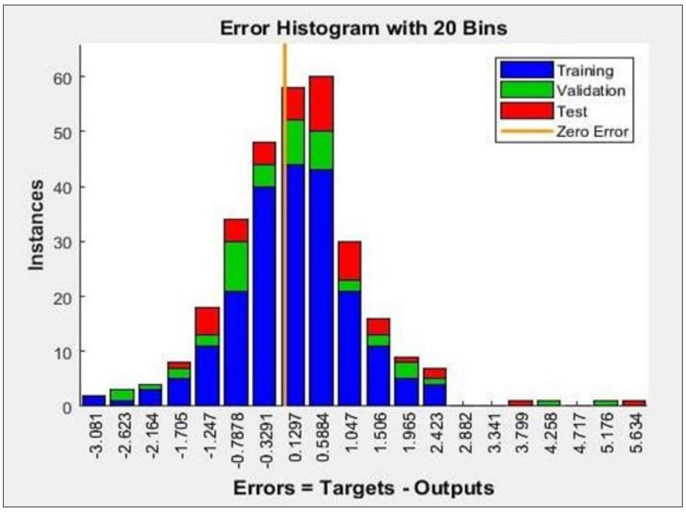

Figure 11 Error histogram of model 12 for ϕ prediction

3.6. ANN Model Equations and Performance Evaluation

In this study, the application of a sigmoid function, specifically the hyperbolic tangent sigmoid function (tansig), was central to the development of Artificial Neural Network (ANN) models. This function, pivotal in enabling the ANN models to map complex nonlinear input-output relationships, is represented by Equation 1:

$$Th = F_tansig = f(x) = 2/\left(1 + e^{(-2x)}\right) - 1 \qquad \text{Equation 1}$$

For predicting cohesion (c), Model 7, based on a 5-10-1 network architecture, emerged as the most effective. The model's details, including weights and biases, were outlined in Table 12.

Table 12 Weights and Biases of Model 7 (Network 5-10-1) for c Prediction

	Connection Weights (wih)						**Biases**	
h	**LL(x1)**	**PL(X2)**	**PI(X3)**	**Sand%(x4)**	**Fine%(x5)**	**Vh**	**bh**	**bo**
1	-1.636	-0.484	-0.907	-0.367	1.028	2.162	-0.345	-0.345
2	0.307	-1.630	2.698	0.954	0.935	3.013	0.869	
3	-0.601	0.405	-1.337	3.741	-2.501	3.880	0.683	
4	-1.173	0.187	1.106	0.386	-1.019	0.115	-2.002	

5	1.139	-2.006	1.164	-2.646	0.356	-1.989	0.479	
6	-1.187	-1.834	-0.386	0.804	2.504	-0.031	-0.314	
7	1.793	0.116	0.897	0.221	-2.406	2.799	1.810	
8	-0.922	1.537	1.220	1.734	4.21	-0.351	-1.109	
9	-0.314	2.165	-2.354	3.775	1.461	-2.273	0.337	
10	-0.684	0.589	2.638	-2.005	-3.821	1.971	-2.478	

The model utilized Equation 2 for calculating the weighted sum (wh) for each hidden neuron:

$$wh = bh + \Sigma(wih * xi) \qquad \text{Equation 2}$$

from i=1 to p

The xi values in this equation, representing normalized input variables, were computed using Equation 3:

$$\mathrm{xi} = \frac{(\mathrm{X_norm,max} - \mathrm{X_norm,min})}{\mathrm{X_max} - \mathrm{X_min}}(\mathrm{x} - \mathrm{x_min}) + \mathrm{X_norm,min} \qquad \text{Equation 3}$$

These calculated values were then fed into the sigmoid function (Equation 4) to obtain the normalized c value, which was subsequently converted to real values using Equation 6.

$$\mathrm{Ftansig(wh)} = \frac{2}{1 + e^{(-2Wh)}} - 1 \qquad \text{Equation 4}$$

$$c\ norm = b0 + \textstyle\sum_{h=1} n\,(vh \times Th) \qquad \text{Equation 5}$$

$$c\ norm = \frac{Cnorm - Ynormmin}{\left(\frac{Ynorm,max - Ynorm,min}{Ymax - Ymin}\right)} + Ymin \qquad \text{Equation 6}$$

The prediction of the internal friction angle (ϕ) was conducted using Model 12, following a 5-11-1 network architecture, with details presented in Table 13. The approach for calculating ϕ was like that of the cohesion model, utilizing Equations 2 to 5.

Table 13 Weights and Biases of Model 12 (Network 5-11-1) for ϕ Prediction

	Connection Weights (wih)						**Biases**	
h	**LL(x1)**	**PL(X2)**	**PI(X3)**	**Sand%(x4)**	**Fine%(x5)**	**Vh**	**bh**	**bo**
1	-0.950	-2.303	0.533	-1.468	0.772	1.723	-0.411	1.551
2	1.009	-1.397	1.498	-1.269	1.087	-1.284	0.070	
3	0.933	-1.210	0.506	0.707	-0.248	1.794	-1.650	
4	0.985	-2.457	1.954	-2.256	-0.208	0.211	0.800	
5	-0.823	-0.660	-0.159	-3.117	1.275	2.285	1.189	
6	0.388	-0.385	-0.732	1.794	0.959	-0.144	2.107	
7	0.544	-0.538	1.220	0.778	1.613	0.631	-0.450	
8	0.145	-0.280	2.029	-0.103	-0.599	1.104	0.617	
9	1.691	3.098	-0.853	0.802	0.241	3.589	0.314	
10	1.421	1.551	1.317	1.007	0.682	1.172	0.503	
11	0.443	1.249	-1.516	-0.644	-1.224	2.058	-0.435	

The normalized ϕ values obtained were then transformed into real values using Equation 7.

$$\phi = \frac{\phi norm - Ynormmin}{\left(\frac{Ynorm,max - Ynorm,min}{Ymax - Ymin}\right)} + Ymin \quad \text{Equation 7}$$

A critical component of the research was a comparative analysis with conventional regression models. This involved employing a multivariable linear least square regression (LLSR) approach. Key influencing variables for c and ϕ were identified using a stepwise regression technique, leading to the development of regression models detailed in Equations 8 and 9.

$$C = 20 + 2.18LL - 2.05PL - 2.36PI + 0.06F + \mathcal{E} \quad \text{Equation 8}$$

$$\phi = -29.51 + 0.45F + 0.46S + \mathcal{E} \quad \text{Equation 9}$$

The multiple regression (R) values for both c and ϕ are 0.35 and 0.64 respectively. The R^2 values are 0.12 and 0.41 for c and ϕ respectively. The ANN models were then compared against existing literature models, as seen in Tables 14 and 15. This comparison highlighted the superior accuracy of the ANN models in predicting cohesion and internal friction angle.

Table 14 Comparison of ANN Model and Existing Correlations for c Prediction

Existing Models	**Equation for c**	**R**	**MSE**	**RMSE**
Roy, (2014)	$c = 224.032 - 2.272\ PL - 2.485\ PI$	0.036	72.65	8.52
Ersoy et al., (2013)	$c = 0.265(PI/LL)^{2.78}$	0.108	134.50	11.60
Goktepe et al., (2008)	$c = 1.61 - 0.03\ \omega - 0.01PI$	0.592	94.17	9.70
Current Regression	$20 + 2.18LL - 2.05PL - 2.36PI + 0.06F$	0.35	50.471	7.104
Current ANN	ANN	0.982	1.27	1.12

Table 15 Comparison of ANN Model and Existing Correlations for Φ Prediction

Existing Models	**Equation for ϕ**	**R**	**MSE**	**RMSE**
Roy, (2014)	$\phi = -29.604 + 34.220\ BD$	0.296	175.92	13.26
Ersoy et al., (2013)	$\phi = -204.5(PI/LL) + 56.3(PI/LL) + 31$	0.309	123.52	11.11
Goktepe et al., (2008)	$\phi = -6.38 + 0.58\ \omega + 0.05\ PI$	0.503	295.93	17.20
Current Regression model	$-29.51 + 0.45\ F + 0.46\ S$	0.64	10.173	3.189
Current ANN model	ANN	0.987	1.15	1.07

Table 16 Comparison of existing ANN models with the current model for c prediction

ANN Models	**No. of datasets**	**Soil types**	**R**	**MSE**	**RMSE**
Lyeke et al., (2016)	83	Tropical lateritic soil	0.861	MAE=6.08	8.33
Kiran & Lal, (2016)	200	Sandy silt	0.942	3.97	11.68
Yoseph, (2022)	284	Fine grained	0.974	2.82	1.68
Current model	316	Black cotton soil	0.982	1.27	1.12

Further, the study compared the current ANN models with existing ANN models, focusing on the impact of dataset size on model accuracy. Tables 16 and 17 illustrated this comparison, indicating that the current models, which had the largest dataset, exhibited the highest accuracy for predicting soil shear strength parameters.

Table 17 Comparison of existing ANN models with the current model for ϕ

ANN Models	No. of datasets	Soil types	R	MSE	RMSE
Lyeke et al., (2016)	83	Tropical lateritic soil	0.805	MAE=4.34	4.77
Kiran & Lal, (2016)	200	Sandy silt	0.981	5.65	6.04
Yoseph, (2022)	284	Fine grained	0.965	1.72	1.31
Current model	316	Black cotton soil	0.987	1.15	1.07

In summary, the study effectively demonstrated the superiority of the developed ANN models over traditional regression models and existing ANN models. The detailed mathematical framework, including the crucial role played by various equations, was pivotal in achieving high accuracy and reliability in predicting soil shear strength parameters.

4. Conclusion

In conclusion, the study's pivotal accomplishment was the development of Artificial Neural Network (ANN) models aimed at estimating soil shear strength parameters, specifically cohesion (c) and internal friction angle (ϕ), based on soil index properties. A comprehensive analysis of 316 soil test results led to the determination of optimal ANN configurations: for cohesion, a 5-10-1 network (five inputs, ten hidden layer nodes, and one output node) was identified, yielding a high correlation coefficient (R) of 0.99 for testing data and a Mean Squared Error (MSE) of 1.27. Similarly, for the internal friction angle, a 5-11-1 network was found most effective, with an R value of 0.98 and an MSE of 1.15 for testing data. These results are significant as they demonstrate the models' precision and robustness. The R values, being close to 1, indicate an excellent fit between the predicted and actual data, affirming the accuracy of the ANN approach. Concurrently, the minimal MSE values underscore the models' reliability in predicting soil shear strength with minimal error. Particularly relevant for soils akin to those in Bishoftu, Ethiopia, these models offer substantial improvements over traditional empirical methods. For future research, the study suggests broadening the dataset to include a variety of soil types and incorporating other influential factors such as organic content and stress history. This expansion would not only enhance the accuracy and applicability of the models across different regions and soil conditions but also advance the capability of ANN models in predicting soil shear strength with greater precision and reliability.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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