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Predicting Of Ultimate Bearing Capacity from Shear Strength Parameters Using Artificial Neural Network

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ABSTRACT: It is necessary to determine the bearing capacity of soil through the process of geotechnical investigations prior to the design of foundation. However, soil investigation is often neglected or rejected by most people on the basis of cost despite the fact that the cost of carrying out geotechnical investigations for a project is negligible compared to the total cost of the project. Terzaghi's equations is the most widely used for the determination of ultimate bearing capacity of soil. This research focused on the specific contribution of cohesion and angle of internal friction to bearing capacity of soils making used of Terzaghi's equation the cohesion and angle of internal friction were used to predict the ultimate bearing capacity of using ANN.Therefore, implementing soft computing techniques in the analysis of foundation soil and developing models from the existing data will bridge the gap and minimize these challenges. Based on that, this research relates the data of shear strength parameters collected from the secondary source and predicted values from the models developed using ANN. The value of correlations obtained from ANN strip, square and circular footing respectively, in training (R^2 = 0.9684,0.9687,0.98575), validation (R^2 = 0.98689,0.91771,0.99298), testing (R^2 = 0.97583,0.91771,0.97348), and All (R^2 = 0.97126,0.96755,0.98512). The established relationship between parameters used indicates the suitability of applying both models in predicting shear strength parameters of foundation soil. Although, ANN result has shown a high accuracy based on the correlation values obtained.

Keywords: neural network, cohesion, angle of internal friction, footing

I. INTRODUCTION

The nature and manner at which structural buildings are collapsing in Nigeria, causes a serious threat to structural engineers, building industry, government, estate developers, building consultants and other relevant stakeholders in the building industry, as well as landlords. Many cities in Nigeria have high rising structures which generally, require a factor of safety with respect to different building materials, due to the unpredictability in the analysis of soil and its cost implication. This calls for detailed geotechnical investigations of foundation soils so as to guard against reoccurrence of such ugly incidents. Material study of foundation soils to a large extent, serves as preventive measure for foundation failures. Nwankwoala and Warmate (2014), studied the foundation geotechnical properties of a site in Port Harcourt, Aduoye and Agbede (2014) use Terzaghi's equations to determine the bearing capacity of soil samples from Obafemi Awolowo University Campus. They found correlations between angle of internal friction and bearing capacity of the studied soils. Other researchers such as Ola (1988), Ogunsanwo (2002), Ige and Ogunsanwo (2009), Oyedele etal. (2011), Avwenagha et al. (2014) have worked on the geotechnical properties of foundation soils in Nigeria. The soil bearing capacity is defined as the capacity of the underlying soil to support the loads applied to the ground without undergoing shear failure and without accompanying large settlements B.M. Das, (2002). The theoretical maximum pressure which can be supported without failure is called ultimate bearing capacity, while the allowable bearing capacity is the ultimate bearing capacity divided by the factor of safety.

The established theory on ultimate bearing capacity is based on ideal condition of soil profiles. In reality, the soil profiles are not always

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homogenous and isotropic. Therefore, rational judgment and experiences are always necessary in adopting proper soil parameters to be used in calculations of ultimate bearing capacity. The pioneer to propose the early theory to evaluate bearing capacity of soil is Terzaghi K. Terzaghi, (1943). The ultimate bearing capacity expressed by Terzaghi, using equilibrium analysis.

$$q_{ult} = CN_C + \Upsilon DN_\Upsilon + 0.5BN_\Upsilon \ldots\ldots\ldots\ldots\ldots(1)$$

$$q_{ult} = 1.3CN_C + \Upsilon DN_\Upsilon + 0.4BN_\Upsilon \ldots\ldots\ldots\ldots(2)$$

$$q_{ult} = 1.3CN_C + \Upsilon DN_\Upsilon + 0.3BN_\Upsilon \ldots\ldots\ldots\ldots(3)$$

Equations (1-3) are Terzaghi' bearing capacity (in kN/m2) equations for shallow strip footing, shallow square footing and shallow circular footing respectively; where: c = cohesion of soil (kN/m2), γ = effective unit weight of soil (kN/m3); D = depth of footing (m), B = width of footing (m). Values of bearing capacity factors Nc, Nq, and Nγ for different angles of internal friction, as proposed.

N_C, N_q, N_γ: are Terzaghi bearing capacity coefficients obtained from friction angle (ϕ)
C: Cohesion of soil
q: overburden pressure
γ: density of soil
B: width of foundation

II. METHODOLOGY

2.1 Data Collection

The data was obtained from Bayero university Kano, Ministry of works kano state, Kano University of Science and Technology Wudil, department of civil engineering library and previous research. The data is a secondary data which contains shear strength parameters that is cohesion and angle of internal friction (c, ϕ) and ultimate bearing capacity.We used seven previous projects in the gathering of data and we collected 45 set of data in KUST Wudil, 115 set of data BUK Kano, 15 set of data ministry of works kano state and 25 set of data from previous research.

In this researched 200 data were used, 175 for training models and 25 were used for the testing of the models.

2.2 ANN Simulation

ANN is a model designed based on a mathematical model to process information which resembles brain in learning process and synaptic weight (Kuo-lin Hsu et al., 1995; Muhammad et al., 2014). In the ANN, information processing occurs at many single elements called nodes (neurons), which are passed between the nodes through the link, each connected link having an associated weight, which represents its connection strength to determine the output signal, the activation function, should be applied to each node of the nonlinear transformation (Committee 2000). ANN can be categorized in term of learning method, flow of information and objective function (S.I Abba et al, 2017). Among the various classifications of ANN, Feed-Forward Neural Network (FFNN) with Back propagation (BP) is widely used and the most common one, each training input data is flow through the system and passed to the out put layer, after the training error is generated which is propagated back to the network until the desired output is achieved. The main concept is to minimize error, so that the network learns the training data (Committee 2000; Nourani et al., 2013; Muhammad et al., 2014). The detail information about BP can be obtained from (Sharifi et al., 2009; Committee 2000; Muhammad et al., 2014; Nourani et al., 2013). As shown in Fig. 1, It has been used to estimate and simulate functions with BP three-layer FFNN, which are used to define a set of input and output parameters between non-linear function mappings to provide an overall framework (Nourani et al., 2015)

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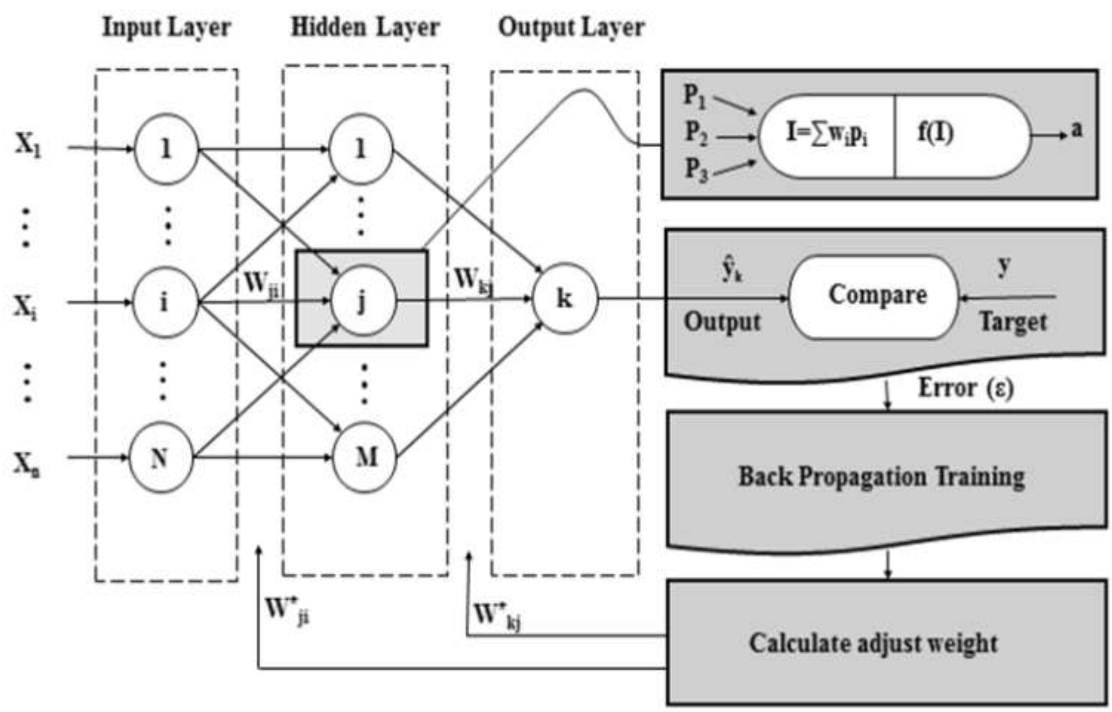

Figure 1: A three-layered feed-forward neural network with BP (Nourani et al,2015)

2.3Multilayer Perception Network

Many different training schemes for ANN are available in literature. The Bayesian regularization was applied to back-propagation neural network for prediction. To train the network, 123 datasets out of 175 were used for training data, 26 datasets for validation and 26 datasets for with two nodes of input parameters in the network architecture, the input parameters are taken as cohesion (C) and angle of internal friction (phi) and one output parameter as ultimate bearing capacity

2.4 Output Performance Criteria

This research used various statistical error measure criterions like R, MAE and RMSE to compare different developed models. A good model should haveR value (expresses degree of similarity between predicted and actual values) close to 1 and low MAE and RMSE values (indicate high confidence in model-predicted values).

According to Abba et al (2019), the model efficiency performance should include at least one goodness-of-fit (e.g., R^2) and at least one absolute error measure (e.g., RMSE), Therefore, in order to assess the predicting efficiency of the models.

Root mean-squared error (RMSE) is used to compute the square error of the prediction compared to actual values as well as the square root of the summation value. Thus, the RMSE is expressed using the following equation:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_p - y)^2}\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Mean Absolute Error (MAE) is a measure of errors between paired observations expressing the same phenomenon. The mean absolute error is given by

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Yp - Y|\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

The Coefficient of correlation (R) value is a measure of linear relationship between the predictions and the actual values. The R value is calculated using the following formula

$$R = \frac{n(\sum y.y_p)-(\sum y)(\sum y_p)}{\sqrt{[n\sum y^2-(\sum y)^2][n\sum y_p^2-(\sum y_p)^2]}}\ldots\ldots(6)$$

Mean of the observed data = $\tilde{y} = \frac{1}{n}\sum(y_i)$

Total sum of square = $\sum_{i=1}^{n}(y_i - \tilde{y})^2$

Residual sum of square = $\sum_{i=1}^{n}(y_i - y_p)^2$

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Coefficient of determination R^2 $=1-\frac{\text{Total sum of residual}}{\text{Total sum ofsqaure}}$………..(7)

where y and y_p are the actual and the predicted values; $\tilde{y}$ and $\tilde{y}_p$ are average of the actual and the predicted values respectively; n is the sample size

III. RESULT AND DISCUSSIONS

A total of 200 sets of soil samples parameters were collected from various studies. The dataset was divided into two. 175 data sets were used for training the models and 25 data sets for validation.

3.1 Validation of Model

Table 1.0 shows the models bearing capacity and the calculated bearing capacity. To further ascertain the quality of the model, Figure 2 – 4which are plots of model bearing capacity against calculated bearing capacity were used. The plots show that there is strong relationship between the models bearing capacity and the calculated bearing capacity since both have the value of R^2 greater than 0.75 (75 %).

Table 1.0: Model versus Calculated Bearing Capacity

	CULCULATED VALUES USING TERZAGHIS			**CULCULATED VALUES USING ANN MODELS**		
S/NO.	**STRIP**	**SQUARE**	**CIRCULAR**	**STRIP**	**SQUARE**	**CIRCULAR**
1	1405.935	1701.396	1652.472	1302.2	1383.1	1384
2	1228.75	1507.366	1477.774	1147.5	1210.1	1323.7
3	1558.12	1944.916	1919.86	1483.5	1535.3	1795.7
4	1023.662	1292.2226	1284.3602	889.3969	1131.3	1384.6
5	624.095	793.94	792.104	545.1703	726.379	844.3708
6	448.782	574.6236	574.3212	501.4542	648.4903	613.465
7	391.563	503.0964	503.0748	533.8185	638.4417	562.1944
8	377.1	484.83	484.83	595.0094	650.5697	567.103
9	1230.839	1487.4152	1446.0944	1122.8	1224.4	1227.1
10	1420.294	1745.7712	1710.8224	1346.4	1389.6	1512.7
11	1044.044	1298.8832	1283.5904	951.5281	1082.5	1257.6
12	984.501	1245.0528	1238.4216	844.6184	1091.8	1360.1
13	583.002	744.9246	743.9742	532.5062	722.1571	825.0494
14	435.118	558.3904	558.2608	548.5036	663.4182	611.8939
15	399.9	514.47	514.47	634.2795	671.1195	600.1811
16	1826.648	2144.4404	2027.0228	1549	1838.6	1518.8
17	940.934	1122.6032	1087.6544	791.3065	952.9754	900.7092
18	914.84	1108.652	1083.596	804.5911	901.3512	941.3348
19	825.857	1026.2786	1015.2842	740.4499	900.2978	1009.4
20	619.866	780.0768	776.1456	556.1769	679.354	850.7611
21	596.752	756.6436	754.3972	531.8603	686.0846	727.4845
22	463.385	590.624	589.868	469.4711	619.364	637.9365
23	485.482	622.3336	622.0312	534.9847	682.4738	668.1024
24	423.063	544.0464	544.0248	576.7627	667.5836	609.6389
25	394.2	507.06	507.06	624.551	666.1109	592.0829

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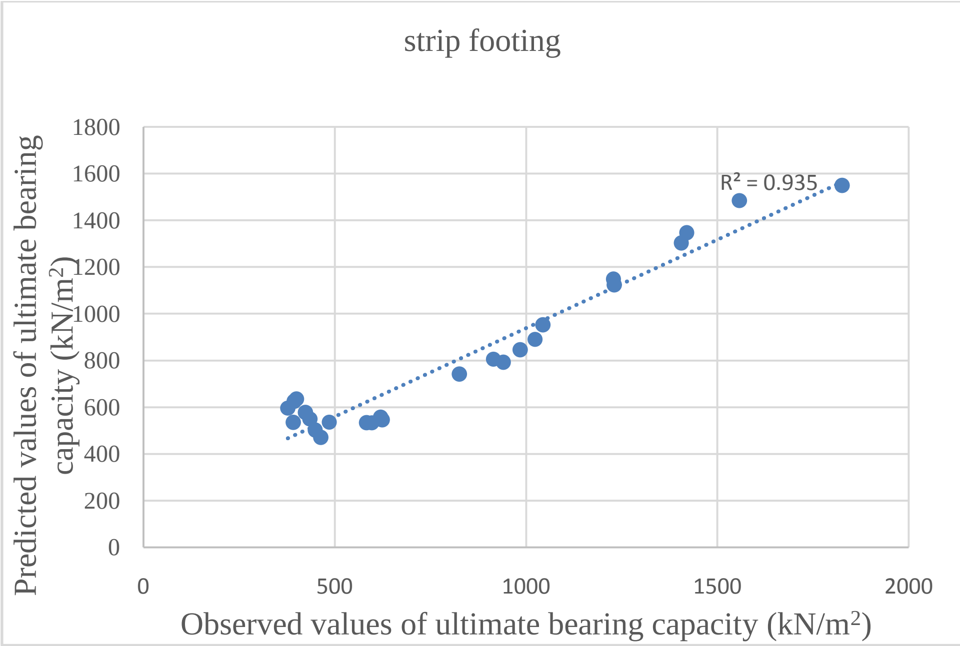

Figure 2.0: Model versus Calculated Ultimate Bearing Capacity for Strip Foundation

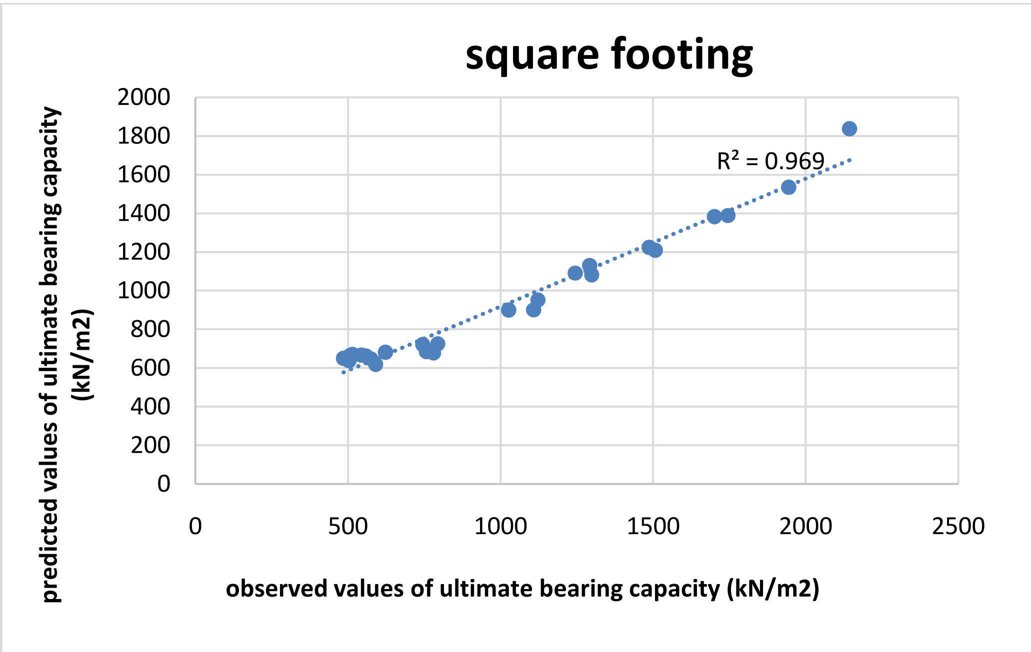

Figure 3.0: Model versus Calculated Ultimate Bearing Capacity for Square Foundation

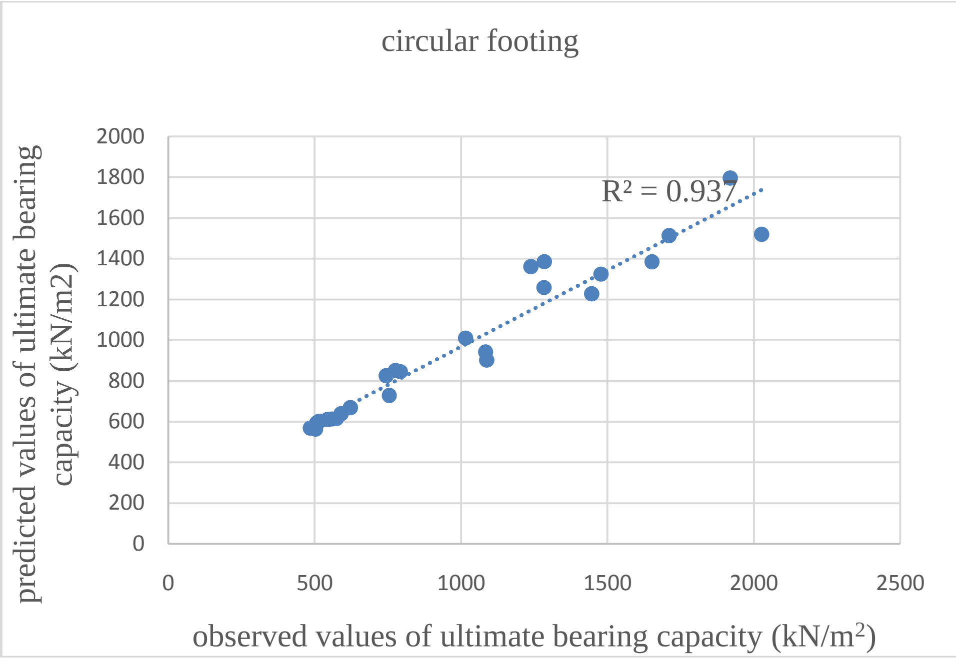

Figure 4.0: Model versus Calculated Ultimate Bearing Capacity for circular Foundation

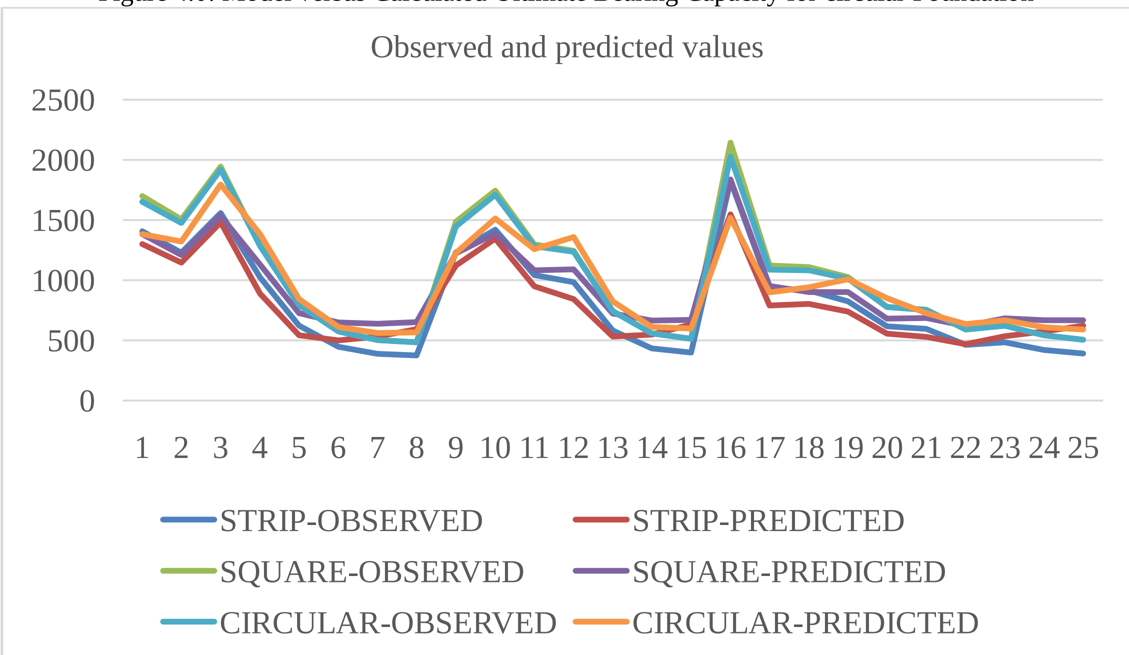

Figure 4.0: Comparison graph of different models

3.2 Performance Criteria

After the training segment of the model has been effectively accomplished, the performance of the trained model should be validated. The purpose of the model validation phase is to confirm that the model has the ability to simplify within the limits set by the training data. The error criteria such as coefficient of correlation (R), the root mean squared error (RMSE), mean square error (MSE) and coefficient of determination (R^2) are often used to evaluate the performance of models. The coefficient of correlation is a measure that is used to determine the relative correlation and the goodness-of-fit between the predicted and observed data as shown in figure 5 and 6.Most popular error measure is the RMSE and has the advantage that large errors receive much greater attention than small errors, Hecht (1990). However, according to Cherkassky et al (2006) RMSE cannot always guarantee that the model performance is optimal.

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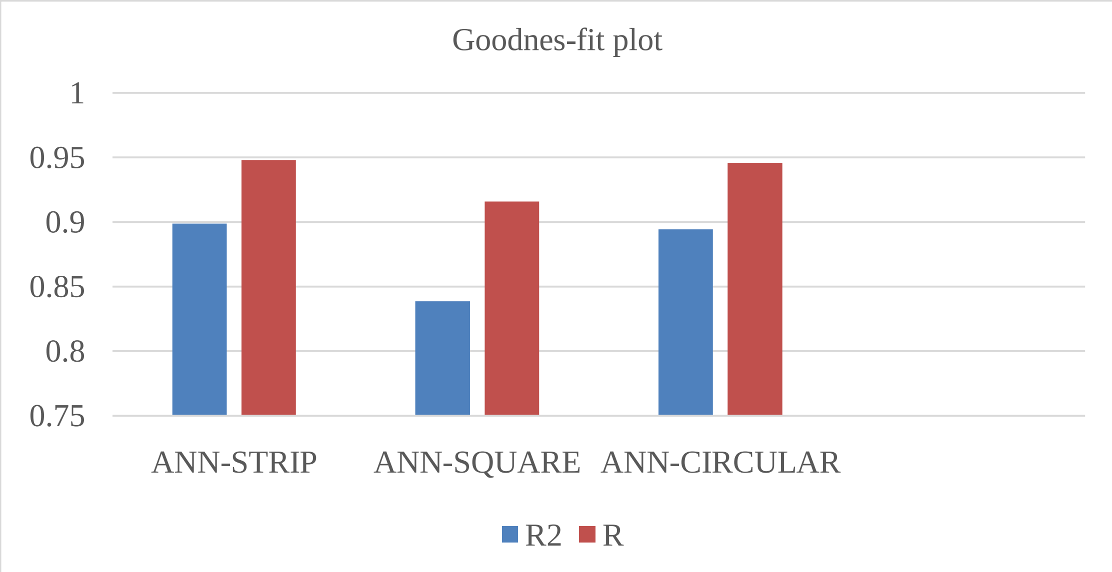

Figure 5.0: Comparison of Performance Criteria of Goodness-Fit

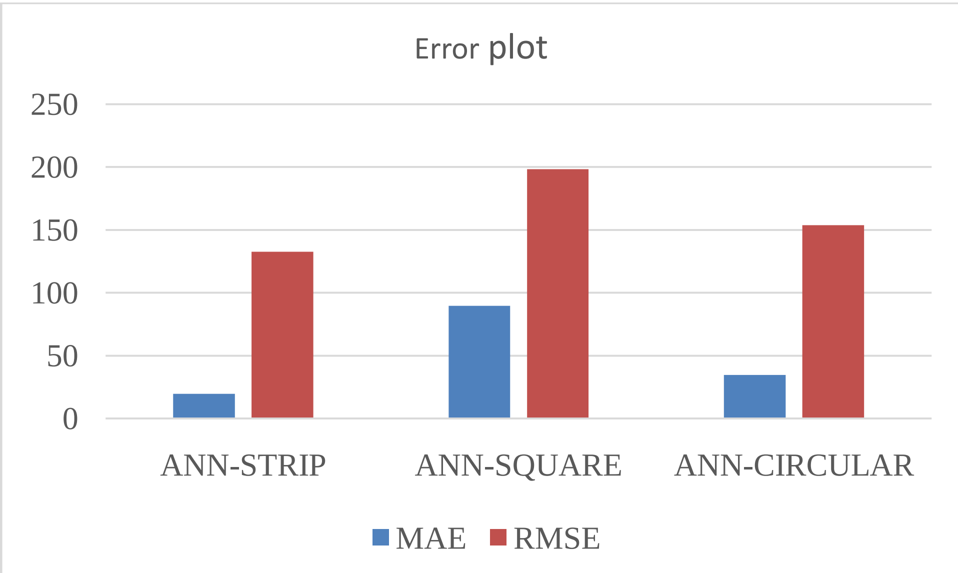

Table 6.0:Comparison of Performance Criteria Error

IV. CONCLUSIONS

1. A data base was developed containing cohesion, angle of internal friction and ultimate bearing capacity of strip, square and circular foundation, with total data set of 200
2. The ANN, has been used in modelling the ultimate bearing capacity of strip, square and circular foundation.
3. 25 independent set of data was used in this study to test the models, it has been seen that ANN models is quite efficient in determining the ultimate bearing capacity of strip, circular and square foundation, it was found that the observed and predicted ultimate bearing capacity of strip, circular and square foundation are close with correlation coefficient.

V. RECOMMENDATION

1. Based on the findings of this research soft computing are very powerful tools to use in modelling the relationship between shear strength parameters and ultimate bearing capacity of shallow foundation.

2. It is also recommended that other soft computing tools can be use in developing the models of ultimate bearing capacity of soils, such as SVM and ANFIS.
3. It is also recommended that other bearing capacity equations apart from Terzaghi's be considered in further studies.

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