Application of Machine Learning Techniques to Predict some Geotechnical Indices in Ekiti State, Southwestern Nigeria

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Abstract

Adoption of a good estimation model for the prediction of subsoils properties before the commencement of a construction project, or at the preliminary stage of project planning is highly imperative. This will mitigate the most unexpected costs incurred during construction which are mostly geotechnical in nature This research aims to use Machine Learning(ML) tools such as Multiple Linear Regression(MLR)Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF) and M5 Tree (M5P) in geotechnical Engineering with a view to correlate Optimum Moisture Content(OMC),Maximum Dry Density (MDD) and Soaked California Bearing Ratio (SCBR) and Unsoaked California Bearing Ratio (USCBR) from the laboratory by conducting tests on 480 disturbed soil samples The principal component analysis (PCA) was used to examine Collinearity problem among the data set. The actual and predicted values of the machine learning (ML) models using root mean square error (RMSE) showed a varied values of RMSE and Coefficient of determination (R^2). The results varied between 0.04 -0.92 and 0.02 – 0.93 for OMC and MDD while SCBR and UNSCBR ranges from 0.16 to 0.94 and 0.01 to 0.92 f respectively. From the fore going RF gave the least values of RMSE as 101.63 and 1.67 and the highest value of R^2 as 0.92 and 0.93. The results showed that these models had R^2 values greater than 90% and the variation of error between the observed and the predicted values of estimated geotechnical parameters was less than ±2. It's concluded that these models will be useful for preliminary design of Civil engineering infrastructure in Ekiti-State, South Western, Nigeria.

Keywords
Machine Learning, Geotechnical indices, Models, Coefficient of determination, Root Mean Square Error

1. Introduction
Empirical correlations are frequently applied in Geotechnical Engineering to assess various engineering parameters of soils. Correlations are generally derived with the help of statistical methods using data from extensive laboratory or field testing. Least Square Regression (LSR), Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF), K. Nearest Neighbor's (KNN) and M5 model trees (M5P) are some of the types of machines learning (ML) techniques currently used for predicting geotechnical indices. These techniques learn from data cases presented to them to capture the functional relationship among the data even if the fundamental relationships are unknown or the physical meaning is tough to explain. This contrasts with most traditional empirical and statistical met hods, which need prior information about the nature of the relationships among the data. ML is thus well suited to model the complex performance of most Geotechnical Engineering materials, which, by their very nature, exhibit extreme erraticism. This modeling possibility, as well as the ability to learn from experience, has given ML methods superiority over most traditional modeling techniques since there is no need for making assumptions about what could be the primary rules that govern the problem in hand. These methods have been widely applied to tackle various civil engineering problems by different authors: (Goh 1995), (Saini et al. 2007), (Siddique et al.2011), (Pal et al.2012), (Puri et al. 2015), (Singh et al. 2016), (Anbazhagan et al.2016), (Prasad et.al. 2017), (Singh et.al. 2017). Most of these geotechnical properties are evaluated in the laboratory and some are estimated in the field.Their calculation requires

a specific laboratory equipment, an experienced geotechnical engineer with a team of skilled technicians. Thus, determination of these properties is costly and time consuming. Also, soil is a highly erratic material a sits performance is based on the processes due to which it is formed. Hence, correlations developed for one region may not be applicable for the other. This ascertains the need to develop region-based correlations to predict geotechnical properties. Experimental affinity measure essential area of the Geotechnical Engineering where it has been applied as a solution to many challenges, interpreting various situation and prediction of the initial unknown data based on other measured parameters during the preliminary geotechnical assessment (Ameratungaetal,2016), (Dyslietal.,2013), (Michelet al.,2013). Prediction of soil engineering properties from their index and state parameters using Machine Learning (ML) approach is not new. Earlier empirical correlations have been developed and the compaction parameters (Ajayietal 2010), permeability (Boroumand et.al.2005) unconfined compressive strength (Gunaydin etal,2010) (Kalkan et.al 2009), angle of shearing resistance (Kayadelen et.al.2009), shear strength (Goktepe et.al.2008), (JainRajeev et.al, 2010), (Korayen et.al. 1996), (Sivrikaya 2009) bearing capacity (Nejad et.al 2009), resilient modulus (Zaman et.al. 2010), of soils have been related to their index properties such as void ratio, particle sized 10 (size corresponding to 10% finer), % finer than 425-micron, liquid limit, plasticity index etc. The CBR has also been related to some of the index properties (KinMak 2006), (Linveh 1989), (Stephens 1990) (Taskiran 2010) (Yildirim et.al. 2011). Some of the correlations, which are found in the literature, areas follow. Black (1962) has given the graph between soil indices Plasticity Index (PI), Liquidity Index (LI) and the CBR, which is applicable for saturated clays. Johnson and Bhatia (1969) have correlated CBR with suitability index, which is a function of plasticity and gradation of soil. Agrawal and Ghanekar (1970) have proposed the relation in the form of an equation: CBR= 2.0-16.0*log (OMC)+0.07*LL.......... (1) where, OMC is the standard Proctor moisture content in fraction and LL is the liquid limit value of the soil. Regression AN analysis is a statistical tool which could be used to predict the correlation between two or more variables, It includes various methods for modeling and analyzing different variables and finally fitting a linear or nonlinear equation, Artificial Neural Networks (ANNs) are artificial intelligence which try to imitate the human brain and nervous system (Alshayeb et.al.2013).Past researchers have made comparative studies between artificial neuron network and multiple linear regression in the field of Geotechnical Engineering; for example,(Harinietal.,2014) compared them for prediction of California Bearing Ratio(CBR) of fine-grained soils;(Boaduetal.,2013; Siddiquietall,2014) tried to predict geotechnical indices from electrical measurements using both models and compared their results. Measurement of the compaction characteristics and California Bearing Ratio (CBR) of soil in the laboratory is neither time-efficient nor cost-efficient. The growing need for a predictive model as an alternative to laboratory testing was the impetus for motivation in this project. In a geotechnical engineering project, an accurate prediction of the maximum dry density (MDD), optimum moisture content (OMC), CBR for soaked and Unsoaked will not only save time, but will also help reduce the costs, cut down on the use of resources, and lessen the required human labor. The key purpose of this research was to develop an advanced mathematical model that can explain the relationship between the physical properties of fine-grained soil and each of its compaction properties. Furthermore, a comparative study was undertaken to determine the models that produced the best results. The analyses were focused primarily on artificial neural networks, support vector machines, Random Forest, MS Tree along with multiple linear regression models, to make the comparative study more meaningful and, at the same time, more intriguing.

2.0. Materials and Methods

2.1. Location of the Study area

The location where sample materials for this study was obtained is as shown in Fig 1. Soils Samples were obtained from 480 points across the three Senatorial Districts namely : Ekiti North , Ekiti South and Ekiti Central as shown in the legend of figure 1.

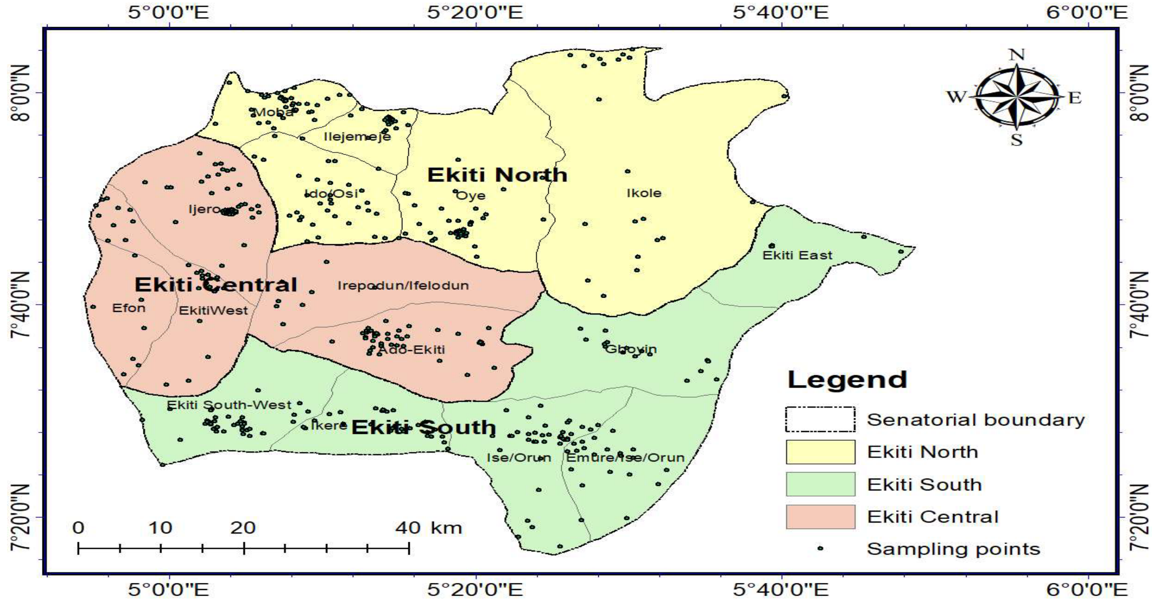

Figure 1. Location of the study area– the three senatorial districts, Ekiti State south western Nigeria.

2.3. Research Materials
The materials used in this study includes global positioning system device (GPS), other materials include, field notebook and data sheets, sample bags, soils sample, sample labels, trowel, spade and scoop.

2.4. Field Procedure, Sampling and Testing Methods
These involved site recognizances of the study area and proper observation of the study areas and subsequent collection of samples for various laboratory analyses. 480 disturbed soil samples were obtained from borrowed pits found within the three Senatorial Districts of Ekiti State Southwestern Nigeria at the average depth of 2m from the ground surface and analyzed for various index and Soil strength (compaction and California Bearing Ratio) properties. Index properties and soil strength tests were analyzed in The Federal Polytechnic Ado-Ekiti (FPA) geotechnical laboratory in compliance with the methods proposed by British Standard BS1377 (1990),

2.5 Data Collection, Division and Analysis for Machine Learning tools (ML)
The application of **ML** rest on the width and Genuity of results selected Is mehenet al. (2017). For these purposes,the results collation and selection are the essential approach that can affect the Machine Learning(ML) function, particularly in the field of geotechnical engineering. The operation of ML model is effectively connected to the dependability and sub-division of input data used and saved in the data bank. In this study, the databank consists of data obtained from various borrowed pits established within the Ekiti-State Southwestern Nigeria. The databank was divided into three parts: training (70%), Testing (30%) and validation (. The training dataset was used in order to train the machine learning models, the validation dataset was used to stop the learning process and all testing dataset were used to assess the Machine Learning (ML) models performance after completion of the training process. Each dataset consists of the factors that affect the output parameters taking into account the five variable that will be selected as input to develop the machine learning models, the variables were Consistency limits symbolized by LL (%), PL (%) NMC, G Sand Percentage passing 75-micron sieve (%) for the prediction of both compactions Parameters (OMC and MDD), SCBR and UCBR. The consistency limits (LL (%) and PL (%)) were selected as input parameters for the four variables of MDD, OMC, SCBR and UCBR as outputs layer. The available data was divided into their sub-sets, the input and output data were pre-processed and normalized between -1.0and1.0.

R studio version 1.2.5033 was used for this research work [R Core Team 202]. In order to reduce the large dimension of the dataset, Principal Component Analysis (PCA) was introduced to solve the multicollinearity problem to ensure no significant relationship exist among the predictors.

2.6. Principal Component Analysis (PCA)
The principal components are the linear combinations of the original variables that account for the variance in the

data. The maximum number of components extracted always equals the number of variables. The eigenvectors, which are comprised of coefficients used to calculate the principal component scores. The coefficients indicate the relative weight of each variable in the component. Principal Component Analysis is based on only independent variables. So, the dependent variable was removed from the dataset.

2.7. Model Performance Evaluation

The performance of the developed machine learning models was evaluated to ensure that the model can perform generally within the pre-defined limits set by the data used for training instead of being peculiar to the input–out put relationships contained in the training data. The Correlation Coefficient R and the root Mean Square Error (RMSE) were used to measure the performance of the predictions since the Correlation coefficient is a key function to establish a relative relationship between the expected and the observed data (Shahin et al. 2008). Smith (1986), this was established by plotting the experimented and predicted values on vertical and horizontal axis respectively Piñeiro et al. (2008) for the developed equations to measure their individual efficiency.

3.0. Results and Analysis

From the analysis of index properties the Central Senatorial Districts soils were classified into four classes as clay of low compressibility (CL) and clay of high compressibility (CH) according to (USCS,1986) while AASHTO classification system classifies as A-2-4, A-2-6, A-2-7 and A-7-6 with sub grade rating of Excellent to good and Fair to poor respectively. Southern Senatorial Districts samples were classified into Eight as A-2-4, A-2-5, A-2-6, A-2-7, A-4, A-5, A-6 and A-7-5 which describe soils in the study area as Clay gravelly sand silty clay materials while Northern Senatorial Districts were classified into Six classes thus A-2-4, A-2-5, A-2-6,A-2-7, A-6 and A-7-6 respectively.

3.1. Selection of Input Parameters for Estimation of Compaction Characteristics (OMC & MDD) and California Bearing Ratio (CBR soaked and unsoaked)

The successful application of a method depends upon the identification of suitable input parameters. The selection of the input parameters is based on the correlation coefficient (R) with output. The more the absolute value of correlation coefficient is close to value 1, the stronger will be the linear correlation while closer to 0 will be very poor correlation between the tested variable

3.2. Measurement of Interrelationship among the Predictors

It is established that there should not be any significant relationship among the independent variables for prediction when using Multiple Linear Regression. Figure 2 showed a Scatter matrix showing interrelationship among the predictors where the Lower triangles provide scatter plots and upper triangles provide correlation values respectively. **Gravel and Fines**, **Sand and Fines** are highly correlated. Similarly, **LL and PL** are also highly correlated which leads to multi co-linearity issues. Predicting the model based on this dataset may be erroneous. However, one way of handling these kinds of issues is based on principal component analysis (PCA) as shown in Fig..2 and .3 . In the scatter matrix all the obvious relationship among the input variables is gone, hence there exists no multi co-linearity among them. Zero correlation means there is no significant relationship among the predictors. This serves as a good foundation for multiple linear regression analysis.

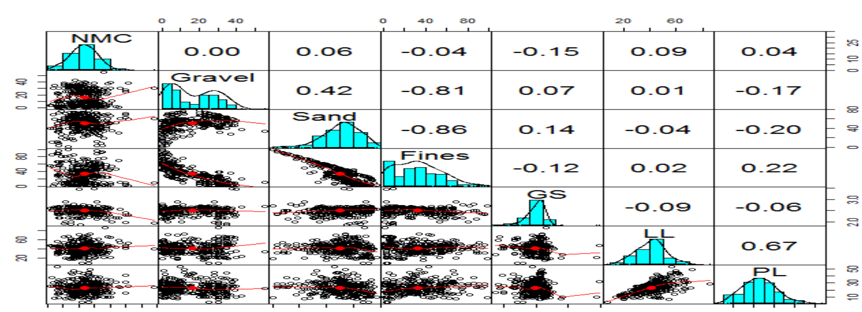

Fig..2. Scattered matrix showing interrelationship among the predictors

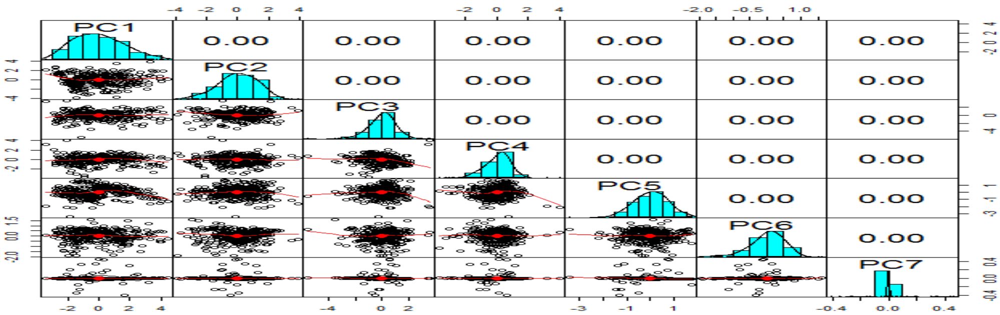

Fig 3 : Scattered matrix showing no relationship among the predictors

3.2 Principal Component Analysis (PCA)

The principal components are the linear combinations of the original variables that account for the variance in the data. It is based only on the independent variables, so we removed the response variable from the dataset. The maximum number of components extracted always equals the number of variables, the eigen vectors, which comprised of coefficients used to calculate the principal component scores. The coefficients indicate the relative weight of each variable in the PCA. The eighth variable is then removed (dependent) from the dataset as shown in Fig. 2 and .3 for OMC, MDD, SCBR and UN-SCBR respectively.

Table 1: Eigen vectors from the PCA

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
NMC	0.0106	0.1877	0.7041	0.6618	0.1735	0.0291	0.0022
Gravel	0.4944	0.1851	0.0097	0.2370	0.6940	0.0826	0.4202
Sand	0.5243	0.1413	0.0184	0.1055	0.6744	0.0381	0.4872
Fines	0.6049	0.1916	0.0104	0.0630	0.0483	0.0704	0.7655
GS	-0.1361	0.1102	0.6698	0.6996	0.1694	0.0515	0.0021
LL	0.1431	-0.6968	0.1244	-0.0292	0.0128	0.6910	0.0007
PL	0.2751	-0.6133	0.1991	0.0233	0.0471	0.7112	0.0000

Table 2 Eigen Analysis of the Correlation Matrix

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Standard deviation	1.596	1.2718	1.0581	0.919	0.75974	0.54974	0.0634
Proportion of variance	0.3639	0.2311	0.1559	0.1208	0.08055	0.04317	0.00057
cumulative proportion	0.3639	0.5949	0.7549	0.8757	0.95625	0.99943	1.00000

The first principal components explain the variability around 36 %, second 23 %, third 16 %, and fourth 12 %. Summarily, the first four principal components capture the approximately 88 % of the variability which is a majority of the variability as shown in table .2. In this case, the resulting Four components score variables are representative of, and can be used in place of the seven original variables with a 12 % loss of information, while the remaining components contribute negligible variability. In these results, the scores for the first four principal components can be calculated from the standardized data using the coefficients listed under PC1 to PC4 as shown in Table .1 and .2 considered.

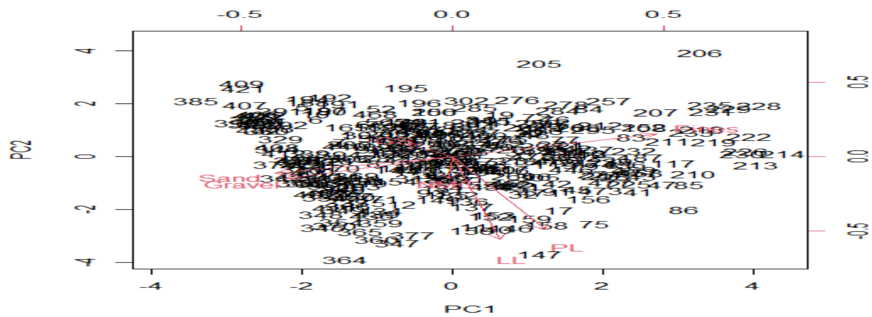

Fig 4. : Bi-plot of the components

3.3 Principal Components Analysis (PCA) Bi-plot

Figure 4 showed the loading plot which is used to identify which variables have the largest effect on each component. Loadings can range from -1 to 1. Loadings close to -1 or 1 indicate that the variable has strongly influenced the component while Loadings close to 0 indicate that the variable has a weak influence on the component. Evaluating the loadings can also help to characterize each component in terms of the variables. In this case, Fine has a high positive relationship with the PC1 while PL and LL also have high negative relationship with PC2 as shown in fig 4 and models equations .1 to 4 showing general Predicting models with Principal Components.

$$PC1 = [\,-0.0105(NMC) - 0.494(Gravel) - 0.52(Sand) + 0.605(Fines) - 0.136(GS) + 0.1431(LL) + 0.2751(PL) \quad (.1)$$

$$\widehat{PC2} = -0.1877(NMC) - 0.1850(Gravel) - 0.1412(Sand) + 0.1916(Fines) + 0.1102(GS) - 0.6968(LL) - 0.6132(PL) \quad (.2)$$

$$\widehat{PC3} = -0.7041(NMC) + 0.0097(Gravel) - 0.0184(Sand) + 0.0104(Fines) + 0.6698(GS) + 0.1244(LL) + 0.1991(PL) \quad (.3)$$

$$PC4 = 0[\,.6618(NMC) - 0.2370(Gravel) + 0.1055(Sand) + 0.0630(Fines) + 0.6995(GS) - 0.0292(LL) + 0.0232(PL) \quad (.4)$$

The derived Model is given below as theoretical and estimated model in equations (.5) to (.8) and equations (.9) to (.12) for OMC,MDD, SCBR and UN-SCBR respectively, where the first four principal components were adopted since the majority of the information are present in the four components. The resulting four component score variables are representative and can be used in place of the seven original variables with a 12% loss of information.

The theoretical model for MDD

$$MDD = \boldsymbol{\alpha} + \boldsymbol{\beta_1}(PC1) + \boldsymbol{\beta_2}(PC2) + \boldsymbol{\beta_3}(PC3) + \boldsymbol{\beta_4}(PC4) + \boldsymbol{\epsilon}. \quad (.5)$$

The estimated model with actual coefficients for MDD

$$MDD = 1907.25 - 1.13(PC1) + 10.22\{PC2\}) + 12.48\{PC3\}) - 35.24\{PC4\}) \quad (.6)$$

The theoretical model for OMC

$$OMC = \boldsymbol{\alpha} + \boldsymbol{\beta_1}(PC1) + \boldsymbol{\beta_2}(PC2) + \boldsymbol{\beta_3}(PC3) + \boldsymbol{\beta_4}(PC4) + \boldsymbol{\epsilon} \quad (.7)$$

The estimated model with actual coefficients for MDD

$$OMC = 14.23 + 1.01\{PC1\}) + 0.5\{PC2\}) - 0.29\{PC3\}) - 0.24\{PC4\}) \quad (.8)$$

The theoretical model for Soaked California Bearing Ratio (SCBR)

$$SCBR = \boldsymbol{\alpha} + \boldsymbol{\beta_1}(PC1) + \boldsymbol{\beta_2}(PC2) + \boldsymbol{\beta_3}(PC3) + \boldsymbol{\beta_4}(PC4) + \boldsymbol{\epsilon} \quad (.9)$$

The estimated model with actual coefficients for Soaked California Bearing Ratio (SCBR)

$$SCBR = 35.14 - 7.5(PC1) - 3.88(PC2) + 0.13(PC3) - 6.67(PC4) \quad (.10)$$

The theoretical model for UN-Soaked California Bearing Ratio (USCBR)

$$USCBR = \alpha + \beta_1(PC1) + \beta_2(PC2) + \beta_3(PC3) + \beta_4(PC4) + \epsilon \quad (.11)$$

The estimated model with actual coefficients for UN- Soaked California Bearing Ratio (USCBR

USCBR = 57.99 - 5.29 {PC1}) - 1.68 {PC2}) + 2.06 {PC3}) - 2.46 {PC4}) (.12)

3.5 Measures of Accuracy between the Actual and the Predicted Values (Goodness of fit) for OMC, MDD, SCBR and UN-SCBR

The Correlation Coefficient R and the Root Mean Square Error (RMSE) are the major yardsticks that are usually adopted to measure the performance of any prediction where the Correlation coefficient is a key function to establish a relative relationship between the expected and the observed data (Shahin et al, 2008). (Smith, 1986) prepared the following guide to measure R ─/R/≥0.8 Strong correlation, ─0.2< /R/ < 0.8 Correlation exists, /R/≤0.2 Weak correlation and /R/ = 0 No correlation. The statistical results from the actual and predicted values of the machine learning (ML) models using Root Mean Square Error (RMSE) showed the varied values of RMSE as 253.84, 295.44, 218.08, 101.63, 211.12 and 3.91, 4.55, 3.54, 1.67, 20.13. are from MLR, ANN, SVM, RF, and M5 model for MDD and OMC values respectively while Coefficient of determination (R^2) varied between 0.04 -0.92 and 0.02 – 0.93 for OMC and MDD respectively. From the fore going RF gave the least values of RMSE as 101.63 and 1.67 and the highest value of R^2 as 0.92 and 0.93 for MDD and OMC respectively. Similarly, the SCBR and UNSCBR for RMSE ranges between 21.6, 21.23,295.67,7.03,14.54 and24.43,24.59,326.49,8.63,17.7 from MLR, ANN, MS Tree, RF, and SVM models while Coefficient of determination (R^2) varied between 0.16 to 0.94 and 0.01 to 0.92 for SCBR and UNSCBR respectively as shown in figure 5 to 8 . The RF model also showing the least values of RMSE as 7.03 and 8.63 on the other hand showing the highest value of R^2 as 0.94 and 0.92 for SCBR and UNSCBR respectively.

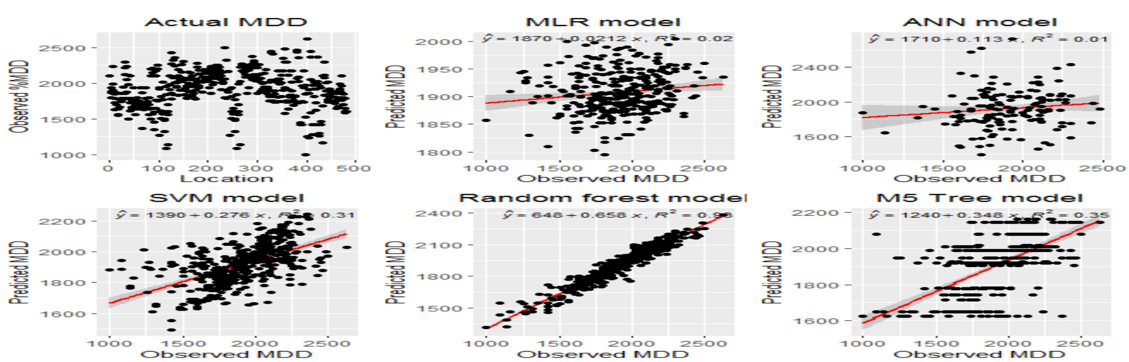

Fig 5: Scattered plots for the performance analysis of the models for predicting Maximum Dry Density (MDD kg/m^3)

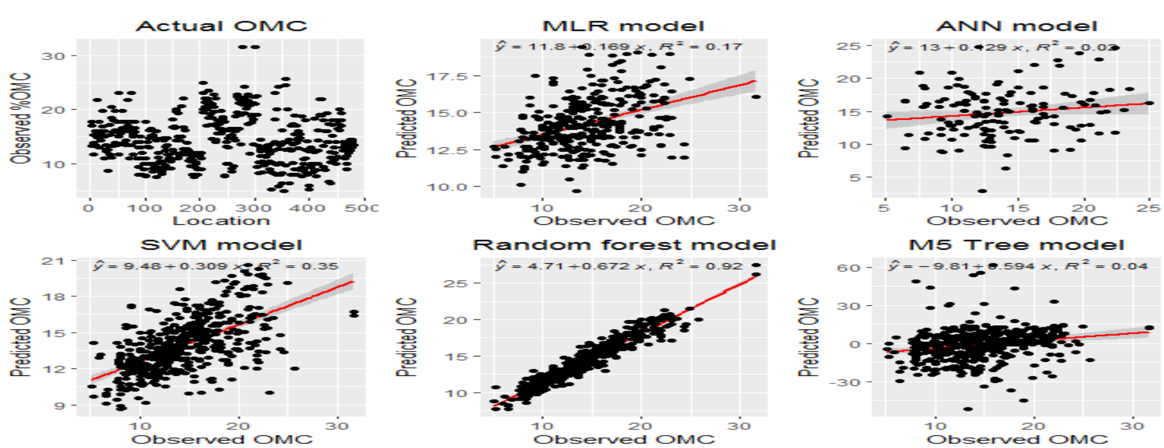

Fig 6 : Scatter plots showing performance of the model in terms of correlation coefficients for Optimum Moisture Content (OMC %).

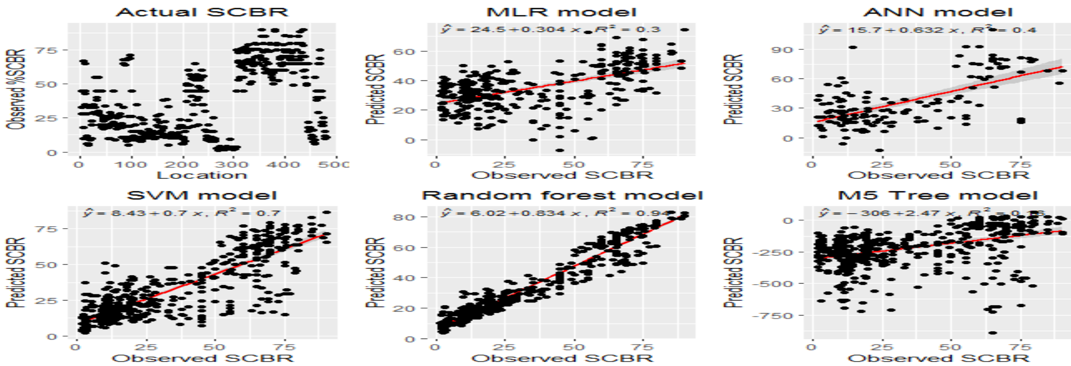

Fig 7 : Scatter plots for the predicting performance of the models in terms of coefficients of determination for Soaked California Bearing Ratio (SCBR)

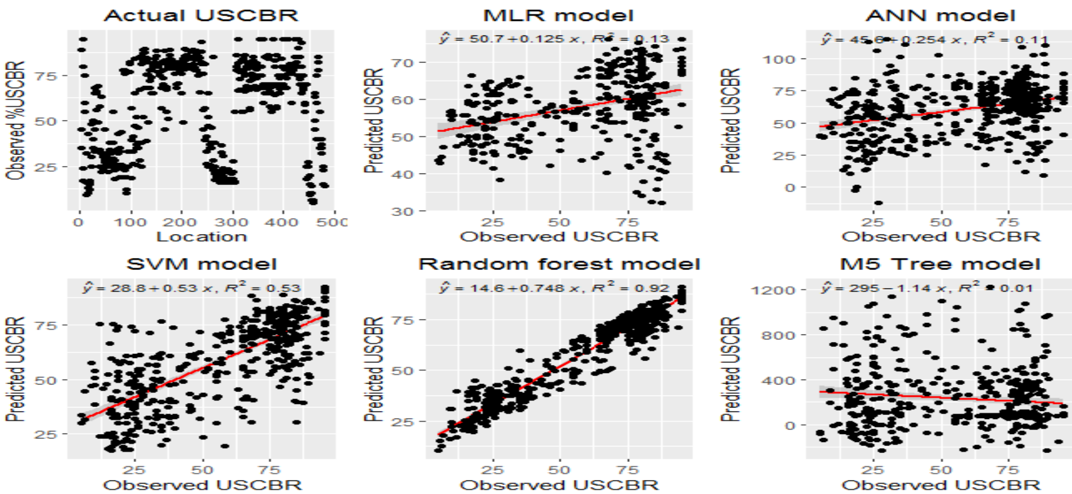

Fig 8: Scatter plots for the predicting performance of the models in terms of coefficients of determination R^2 for UN-Soaked California Bearing Ratio (UN-SCBR)

4.3.8 Comparison of Models Results

The predicted values generated by Random Forest (RF) model seems to move side by side with the actual MDD, OMC, SCBR and UN-SCBR while the MS Tree gave a worst performance as shown in figure .5 to 8 respectively, where the coefficient of determination ($R^{2)}$ from Random Forest (RF) gave 0.92, 0.93, 0.94 and 0.92 for MDD, OMC, SCBR and UN-SCBR respectively. From the foregoing, its concluded that the strength of the developed models after comparison in terms of regression coefficient (R^2) and Root mean square error (RMSE) values. Its is established that all the Machine Learning (ML) model technique predict OMC, MDD and CBR close to the experimental value. However, the prediction of OMC, MDD and CBR by Random Forest (RF) is found better compared to other technique evaluated.

4.0 Conclusion

Application of Machine Learning Techniques has been deployed to Predict some Geotechnical Indices in Ekiti State, Southwestern Nigeria. The comparison of the results between the machine learning tools used in this study revealed the efficiency of RF model which yielded the best goodness of fit in term of R^2 and RMSE. . The study showed that the develop models for RF are strongly correlated for all the four geotechnical parameters predicted that it has a high correlation coefficient varying between 0.9222 and 0.9444 for OMC ,MDD, Soaked and Unsoaked CBR respectively. The basic advantage of machine learning application to estimate geotechnical parameter in the region under study is to help researchers, Consultant and practicing engineers, without considering their proficiency, interested in the problem of modelling to predict OMC, MDD , Soaked and Unsoaked CBR with advantages of gaining time and money.

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Engr. Prof. Jacob Odeh Ehiorobo is a professor of applied geomatic, Water resources and environmental system engineering. He is a professor in the Department of Civil Engineering, University of Benin, Edo- State Nigeria. He has held several administrative positions in the university such as Dean of Faculty of School of Environmental, Director of External Linkage for the University and Deputy Vice Chancellor Administration. Upon graduating with Bsc, Msc and PhD as a prolific researcher he has publish over 100 papers in peer-reviewed journals, conferences and workshops at both local and international level. Engr. Prof. Jacob Odeh Ehiorobo research interest includes: Deformation Surveys and Analysis, Precise engineering surveys, GNSS Positioning and Geodetic Surveys . Remote sensing and GIS Applications in Disaster Monitoring and Control, Water Resources Modeling and Environmental Hazards Analysis, Highway and Transportation including Automatic Vehicle location.

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Engr. Dr. Ebuka Nwankwo is an associate professor in the department of civil engineering, faculty of Engineering University of Benin. Dr Nwankwo graduated with a first class honours in Civil Engineering in 2005 from the Federal University of Technology Owerri. After spending some time in the industry, Dr Nwankwo proceeded for his MSc and PhD in Structural Engineering from the Imperial College London. In 2014, he was awarded a PhD from Imperial College. Dr. Nwankwo has published over 35 articles in peer review journals. Dr Nwankwo has been a visiting researcher at the University of Liverpool. He is COREN registered and member of the Nigerian Society of Engineers (NSE). He has been involved in the training and mentoring of young engineers for NSE. He has a wide range of experience in civil engineering design and project management. He has been called up to give his expert opinions on my projects within and outside Nigeria. Dr Nwankwo has also worked as professional structural engineer in Paris. He has been involved in the design of high-rise structures and geotechnical investigations for civil infrastructure.

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