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Soft Computing Models to Predict the Compaction Characteristics from Physical Soil Properties

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HIGHLIGHTS

- Modeling is a feasible approach to estimating the compaction characteristics from soil index properties.
- ANN model outperforms other models in predicting OMC.
- MLR model provides better prediction of MDD.
- PI is a dominant parameter influencing the compaction characteristics.

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ABSTRACT

The compaction of soil is a pivotal matter in almost every earthwork to achieve the densest possible state of the soil. The suitability of soil for earthworks is largely decided by compaction characteristics such as Optimal Moisture Content (OMC) and Maximum Dry Density (MDD). Identifying the compaction characteristics of a large volume of soil in the laboratory requires a while. As a result, determining compaction characteristics from physical soil properties is critical for initial soil assessment. To predict the compaction characteristics of the soil, three different models of the Artificial Neural Network (ANN), M5P-tree, and Multiple Linear Regression (MLR) are used in this work. Particle size and plasticity properties of soil are combined in the models, and seven input parameters consist of gravel, sand, silt, and clay contents, plastic limit, liquid limit, and plasticity index. 1038 datasets are compiled and processed in order to develop the models. To evaluate the effectiveness of the proposed models, several statistical analyses are harnessed, including coefficient of determination (R^2), scatter index (SI), root mean squared error (RMSE), mean absolute error (MAE), and Objective (OBJ) value. Overall, the ANN model outperformed the MLR model in predicting OMC, while the MLR model outperformed it in predicting MDD. Besides this, the sensitivity analyses revealed that the plastic limit has a greater influence on the value of OMC, whereas both sand content and the plasticity index are important in predicting MDD.

1. Introduction

Soil compaction is a crucial component of the construction process in geotechnical engineering since most of the structures, and earth-retaining structures are supported by the soil. The effectiveness of soil compaction may quantify the appropriateness of soils for a particular type of earthwork. The percentage of gravel and sand, the liquid limit, the plastic limit, the grain-size distribution, the shape of the soil grains, the specific gravity of the soil solids, and the quantity and type of clay minerals all impact soil compaction efficiency.

Soil compaction is one of the most practical methods for densifying soils. When soil is compacted, the particles are forced together by compaction force. As a result, there may be an increase in shear strength while diminishing the compressibility and permeability of the soil mass [1]. In the laboratory, compaction tests using the Standard Proctor (SP) or Modified Proctor (MP) methods are harnessed to determine the two most important parameters, Maximum Dry Density (MDD) and Optimum Moisture Content (OMC) [2].

It is vital to identify the compaction characteristics of natural soils to evaluate their appropriateness for earthworks. In this kind of project, a vast volume of soil is necessitated, and obtaining this massive volume with a desired compaction characteristic from a single borrow source is likely to be difficult. Compaction characteristics must be obtained from a laboratory compaction test in these circumstances to determine the suitability of soils collected from various borrows sources. Nonetheless, laboratory compaction tests necessitate a significant amount of time and effort. As a consequence, in order to assess the suitability of the required soils in advance for any such project, it is critical to establish correlations of soil compaction characteristics with such simple physical properties as Atterberg limits and particle sizes. These are obtained through straightforward methods.

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Many studies have been undertaken to evaluate compaction characteristics indirectly by considering physical soil properties. Several correlations have been developed to estimate compaction characteristics utilizing individual soil index properties [3 - 12] or soil fractions [13, 14]. However, other studies have suggested that considering just one input parameter may not be enough to estimate compaction characteristics. As a result, multiple linear regression (MLR) models have been used to predict compaction characteristics depending on multiple basic soil parameters [15 - 17, 14, 2, 18, 19]. Further to that, machine learning techniques were used in some other studies to develop more accurate correlations [20 - 23].

Sinha and Wang [24] demonstrated that using artificial neural networks (ANN) for the prediction of soil compaction characteristics outperforms traditional statistical models, and a reliable prediction can be obtained. Sivrikaya [16] predicted the compaction characteristics of fine-grained soils that used a multilinear regression model (MLR) based on soil index properties and particle sizes. The input parameters considered were gravel content (G), sand content (S), fine-grained content (F), plasticity index (PI), liquid limit (LL), and plastic limit (PL) (PL). The study concluded that, once compared to other index properties, compaction characteristics correlate well with plastic limit. Gunaydin [4] devoted a variety of techniques, including simple-multiple analysis and artificial neural networks, to anticipate compaction characteristics based on soil particle sizes. The study indicated that reliable correlations (R^2 = 0.70 - 0.95) for preliminary design can be procured utilizing both techniques.

Mujtaba et al. [17] as well developed multiple regression analysis models for 110 sandy soils in forecast compaction characteristics based on the uniformity coefficient (Cu) and compaction energy (CE). Tenpe and Kaur [25] investigated artificial neural network (ANN) modelling performance for predicting compaction characteristics concerning soil index properties that use the liquid limit (LL), plasticity index (PI), and compaction energy (CE). What's more, Omar et al. [26] utilised complex mathematical models and novel approaches to foresee the compaction characteristics of fine-grained soil based on a variety of physical properties. Farooq et al. [2] used a multiple regression model to predict OMC. In addition, Saika et al. [8] created a set of regression models for predicting compaction characteristics concerning consistency limits. Karimpour et al. [27] utilized ANNs and MLR on 728 datasets to predict compaction characteristics based on soil type, grain size distribution, liquid limit (LL), plastic limit (PL), and specific gravity at different energy levels. The analysis revealed that fine content has a greater influence on compaction characteristics than other parameters. Besides that, even though ANN models are more effective, MLR models can be more advantageous in predicting compaction characteristics. This is due to the fact that ANN models are black-box in nature. Verma and Kumar [23] utilized a novel application of artificial neural networks (ANN) to estimate the (MP) compaction characteristics of fine-grained soil in a recent study. The laboratory testing of in situ soil samples from a highway construction site yielded 532 datasets. In addition to the index properties test, modified Proctor compaction tests were performed on the gathered soil samples. The Python V3.7.9 platform was used to write the ANN algorithm code for the analysis. The basic physical soil characteristics of gravel (%), sand (%), fine content (FC), percent material retained on 2.0 mm (R2.0 mm), 0.425 mm (R0.425 mm), and 0.075 mm (R0.075 mm), coarse sand (CS), medium sand (MS), and fine sand (FS), liquid limit (LL), and plastic limit (PL) have been used as input parameters.

Moreover, Verma and Kumar [28] aimed at developing a multi-layer perceptron neural network model for predicting the modified compaction properties of both coarse- and fine-grained soils. Similarly, the Python V3.7.9 platform was employed to write the code for the artificial neural network (ANN) algorithm. To predict the modified compaction characteristics, 179 coarse-grained and 69 fine-grained soil datasets are examined, with Gravel (percent), Sand (percent), FC (percent), LL (percent), PL (percent), and PI (percent) as input parameters. The developed models yielded a high correlation coefficient (R), with a value higher than 0.80 for coarse-grained soils and 0.90 for fine-grained soils.

Various statistical and machine learning models were used in the aforementioned studies to predict compaction characteristics from different soil properties for the preliminary assessment of soil suitability for earthworks. Statistical models are simple to use, and output predictions are obtained in the form of equations, which can be useful in the field. Machine learning models, on the other hand, can analyze large amounts of data and identify specific trends and patterns that humans would not be able to visualize. In dynamic and uncertain situations, Machin learning algorithms can be brilliant at processing multidimensional and multivariant data. Only a few studies predicted compaction characteristics using both statistical and machine learning models. Furthermore, in just a few studies, a large number of data points, such as soil index properties and particle size, have been considered. A large volume of data (1038 datasets) has been compiled from prior reports for this work. Multiple Linear Regression, M5P-tree, and Artificial Neural Network models have been used to predict compaction characteristics (OMC, MDD) with respect to soil index properties and soil particle sizes. In predicting compaction characteristics, this work assesses the performance of the models utilized.

2. Research Objective

According to several investigations, an individual index properties parameter cannot be used to predict the compaction characteristics of different types of soil. As a result, numerous datasets from the literature were gathered in order to develop models to predict soil compaction characteristics based on different soil properties obtained from simple laboratory testing, such as the G %, S %, M %, C %, LL %, PL %, and PI %. As a consequence, three distinct models were developed. In this regard, the models' performance can be evaluated, and the influence of various soil properties can be revealed. As a result, the datasets in two groups of training and testing are examined in the models to achieve the study's main objectives:

1) The influence of the physical soil properties on the compaction characteristics will be examined, and the input parameter that plays the most remarkable in determining the value of the OMC and MDD will be identified from a sensitivity analysis.

2) From different statistical assessment criteria, the model with the best performance to predict the compaction characteristics of soil from basic soil properties will be determined and compared with the other models.

3. Methodology

Totally, 1038 datasets were collected from the literature. The data were randomly mixed and split into two groups: training datasets and testing datasets. The training datasets included 70% of the dataset while 30% was for the testing ones. The training data groups were utilized to develop the models. The main objective of the models was to predict the standard Proctor compaction characteristics (OMC and MDD). Later on, the models were examined by utilizing the testing data. Table 1 contains the number of used data from different studies and ranges of the input parameters: gravel content (G %), sand content (S %), silt content (M %), clay content (C), liquid limit (LL %), plastic limit (PL %) and plasticity index (PI %). Further, in the table, the ranges of the measured values of optimum moisture content (OMC %) and maximum dry density (MDD kN/m^3) are included, which are compared with the anticipated values obtained from the models later. These input parameters are used to develop the models, and the performances of the developed models are evaluated by the actual values of output parameters. The procedure of this study is shown by a flowchart in Figure 1 and can be summarized as:

Stage 1: Collecting data

Stage2: Correlating input and output parameters

Stage 3: Splitting data into two groups: 70% training and 30% testing

Stage 4: Developing different models

Stage 5: Evaluating the performance of the models

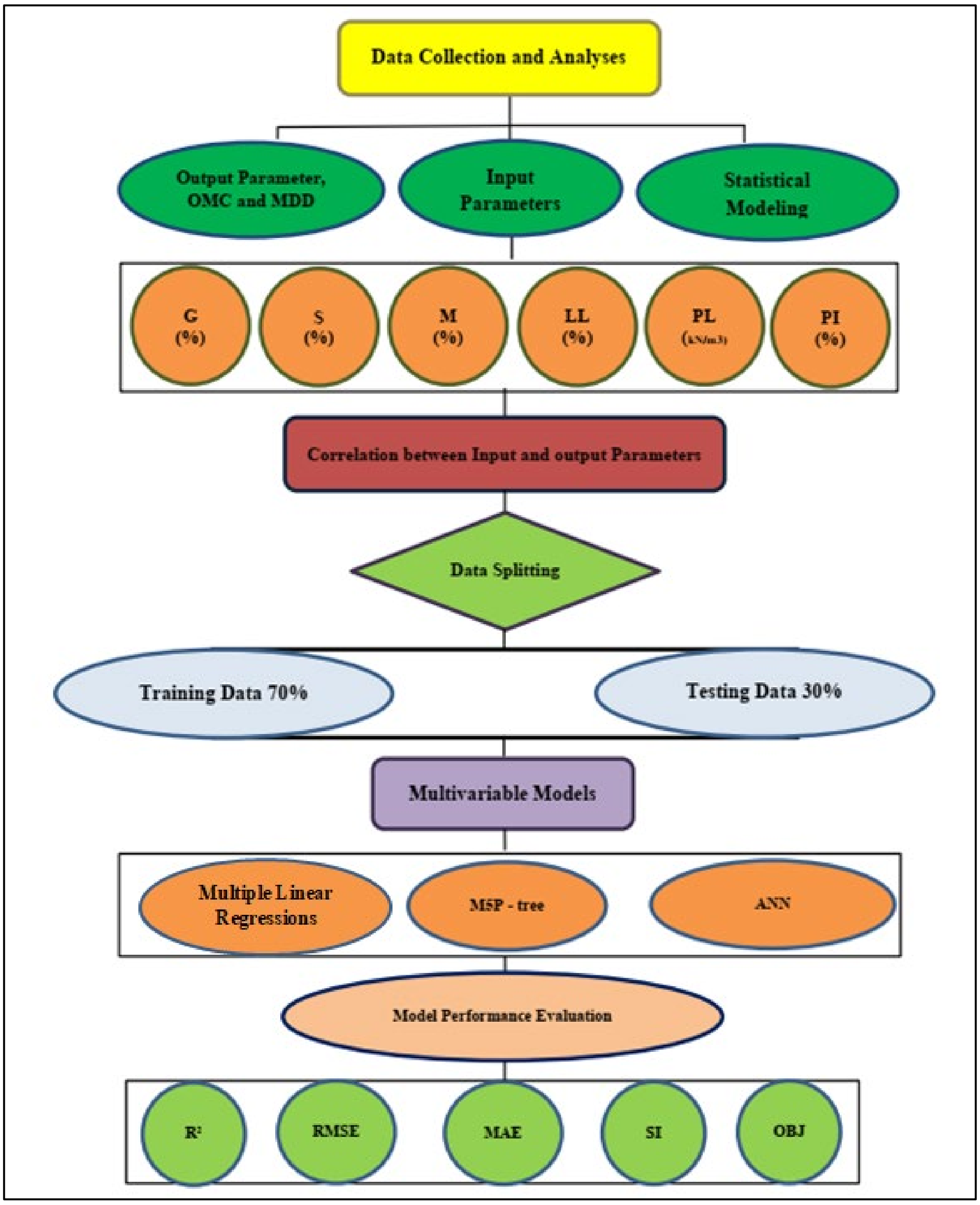

Figure 1: The procedure of the study by a flow chart diagram

Table 1: The range and number of the used datasets

Ranges of Data										Ref.
No. Data	Gravel (%)	Sand (%)	Silt (%)	Clay (%)	LL (%)	PL (%)	PI (%)	OMC (%)	MDD (kN/m³)	
8	0-26	8-46	23-64	3-35	41-53	26-34	15-19	13.5-24	14.7-17.4	[29]
90	0-11.8	17-90.5	1.64-65	4-98	23.5-34	10.3-18	9.1-18	9.5-15.5	17.3-20.8	[30]
25	0-0	5.0-94	9-85	0-59	16-76	16-107	0-45	6.6-32	9.9-21.3	[31]
121	0-26	0-62	15-95	5-59	17-111	7.0-42	1.0-80	8.9-41	12-20.4	[32]
16	0-0	8.4-67.8	15.45-51.7	10.2-48.5	26.6-72.6	10.5-38.1	13.4-39.4	14.8-33	12.7-18.1	[33]
27	0-0	2.0-86	5-50	2-86	44-213	33-167	2.0-58	20-160	4.4-14	[34]
57	0-20	0-100	3-83	6-84	24-495	10.0-47	2-449	8-32.5	12.6-20.8	[35]
15	0-0	5.0-60	14-59	6-72	43-123	22-50	21-100	20.4-49	10.2-16	[36]
88	0-0	1.0-52	28-73	15-46	18-66	12-29	6.0-39	9.0-26	14.6-20.3	[37]
13	0-8	6.0-48	29-58	16-65	24-70	12.0-32	11.0-46	10-24	15.4-20.4	[38]
6	0-0	0-100	5-70	10-95	19-93	12.0-29	4.0-64	8.9-27.7	14.2-19.4	[39]
8	3-28.5	3-28.5	13-48	12-53	18-67	7.0-35	11.0-46	9.0-21	15.5-20.6	[40]
5	0-0	1-13	23.8-58	30-75.5	28.2-98	21.1-40	7.1-58	18.6-32	12.5-16.9	[1]
10	0-0	0-36.5	35.5-88.5	5-51.5	37-73.5	18-51.9	9.5-37.9	16.2-44.4	11.1-17.9	[3]
13	0-0	10.0-50	35-60	15-42	24-48	15-21	9.0-29	12.5-20.5	16.2-19.1	[41]
15	0-0	0-79	5.5-59	6.25-45	31-102	18.5-39	7.0-63	11.0-29	13.5-18.8	[42]
9	0-13.3	0-44.3	28.8-41.9	26.9-64.6	39.7-256.3	6.1-48.2	17.2-217.1	15.6-33.8	12.8-17.6	[43]
92	0-11	0-46	36-88	8-42	25-48	13-29	10.0-24	10.0-22	14.7-19.9	[44]
5	0-3.9	3.1-59	21.2-82.4	5.7-75.2	26-85	14-33	9.0-52	13.5-27.5	14.4-18.5	[45]
54	0-0	15-67	33-85	1.25-45	20.8-58.8	14-38.2	4.7-36.2	12.8-32.4	13-18.8	[46]
5	0-0	0.9-19.6	24.2-87.9	9.6-72.3	30.8-213.3	17.1-44.5	10.3-168.8	15.4-30.1	12.9-17.5	[47]
71	0-35	0.9-47	4-86	1.5-94.3	24-106	15-46	6-71	14-42	10.9-19.4	[48]
15	0-0	3.4-35.1	23.2-56.2	21.2-56.7	33.4-92.4	17.5-42.3	15.9-50.1	20-36.3	11.8-16.2	[49]
42	0-2	2-80	6-76	4-78	24-115	17.4-45.3	3.7-75.6	9.5-36.8	12.6-18.3	[50]
30	0-20.3	4.5-43.9	3.1-38	2.4-76.5	29-77.8	18.2-30	10-55.5	12.0-30	14-19.1	[51]
52	0-0	7.6-71.6	4.3-28.7	18-78	33.8-87.5	15.4-32.3	16.5-55.2	14-24	15.2-20	[14]
10	0.4-5.2	11-34.1	19.3-43.2	38.8-56	31-50	19-37	3-25.4	15-35	11.9-18.3	[52]
7	0-0	6.6-56.5	23.5-49.8	20-43.6	23-41.7	14.9-24.7	5.4-17	14-22.1	13.9-18	[53]
6	0-0	32.5-56.6	19.3-31.3	18-38.5	37.8-87.2	17.7-28	17-69	14.8-24.8	14.4-18.1	[54]
13	0-0	3.6-18.9	59-73.5	11.6-39.6	27.3-61.4	19.6-29	7.3-33	16.5-24.5	14.6-17.7	[55]
4	0-0	1.0-31	32-50	37-53	44-78	18-28	22-57	16-25	14.6-16.4	[56]
8	1.2-9.2	14.9-63.5	20.5-65.9	6.4-56.5	33-81	17-25	8.0-60	14-17	17.9-19.5	[57]
30	0-0	0-60	2-62	5-98	23-227	14.7-39.7	4.0-47	12-29	13.2-18.5	[58]
8	0-2.9	5.2-37	32.2-70.5	28-32.42	63.1-77.4	29.3-37.7	33.6-46.5	17.7-27	13.7-17.2	[59]
8	0-0	17.7-67.8	7.25-28.7	25-62	43.2-76.8	18-25.7	22.9-51.1	15.5-22.5	15.6-19.3	[12]
17	0-9	28-82	7-29	8-69	25-91	15-41	10.0-50	10.4-29.6	13.8-19.2	[60]
7	0-3	1-16	40-59	32-56	40-63	20-30	18-37	16-21	16-18.2	[61]
30	0-7	7.0-26	14-81	7-84	27-32.3	17-22.6	4.9-12.4	11-13	18.9-19.6	[62]

4. Correlations between Input and Output Parameters

The correlations are examined to demonstrate the validity of the correlations between the input parameters and the compaction parameters. The matrix plot in Figure 2 depicted the relationship between the input and compaction parameters in this regard. The Figure demonstrates no strong correlation between the input parameters and the compaction characteristics, except a fair correlation between PL and OMC exists with $R^2 = 0.75$, as shown in Figure 3. This correlation is only valid for fine-grained soils. In other words, in soils where coarse grains (G % and S %) predominate, PL cannot be used to determine

OMC since it does not represent the actual physical behaviour of the soil. Therefore, these index properties are combined to predict accurate compaction characteristics values. Also, the normal distribution of the compaction characteristics data is illustrated in Figure 4. Table 2 shows statistical data such as minimum, maximum, average, standard deviation, skewness, kurtosis, and variance. A high negative value for the kurtosis parameter signifies shorter ends than the normal distribution, while a positive value indicates longer ends. For the skewness parameter, a negative value indicates a left end and a positive value indicates a right end.

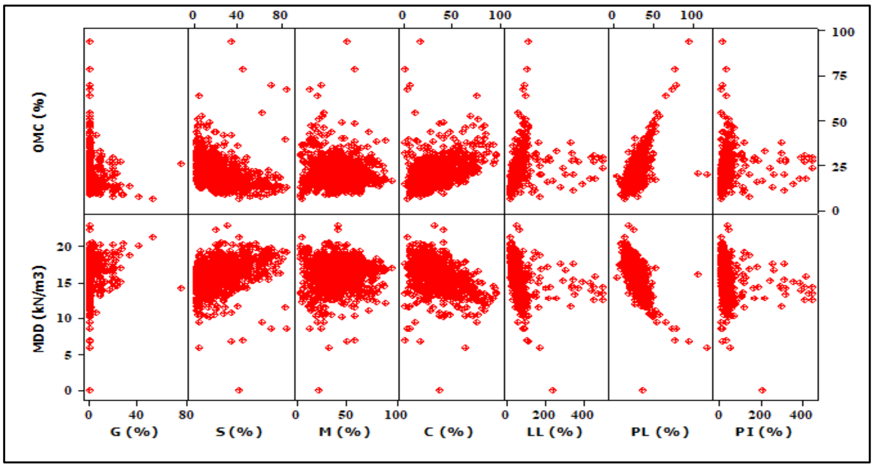

Figure 2: Matrix Plot between the input parameters and the compaction characteristics

	Gravel (%)	Sand (%)	Silt (%)	Clay (%)	LL (%)	PL (%)	PI (%)	OMC (%)	MDD (KN/m3)
Gravel (%)	1.00								
Sand (%)	0.06	1.00							
Silt (%)	-0.16	-0.56	1.00						
Clay (%)	-0.17	-0.41	-0.48	1.00					
LL (%)	0.15	-0.13	-0.29	0.38	1.00				
PL (%)	-0.03	-0.17	-0.21	0.40	0.47	1.00			
PI (%)	0.17	-0.11	-0.27	0.34	0.99	0.33	1.00		
OMC (%)	-0.14	-0.28	-0.12	0.43	0.31	0.75	0.19	1.00	
MDD (KN/m3)	0.16	0.32	0.09	-0.45	-0.38	-0.74	-0.27	-0.87	1.00

Figure 3: Correlation matrix between the input and output parameters

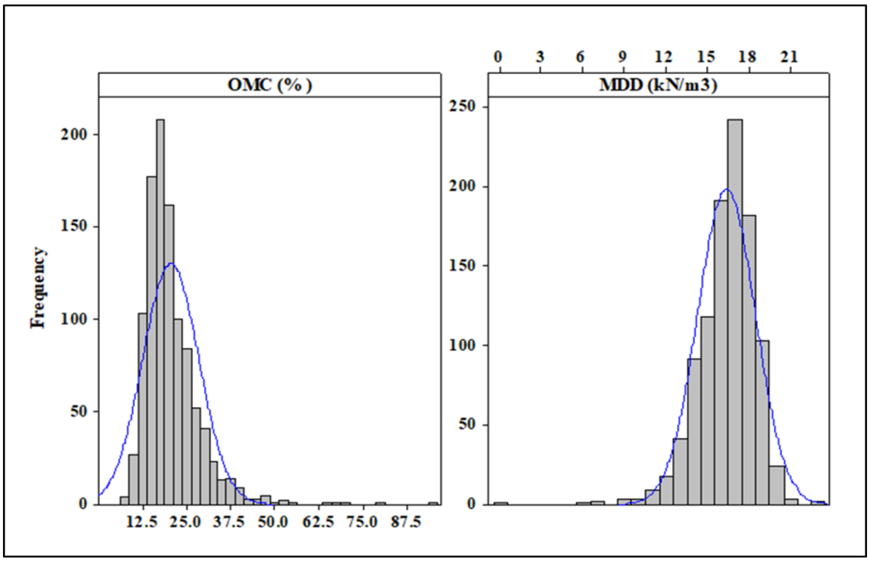

Figure 4: Normal Distribution of the compaction characteristics data

Table 2: Statistical parameters for input and output variables

No.	Variables	Min	Max	Mean	Variance	Standard Deviation	Skewness	Kurtosis
1	G (%)	0	75.8	1.67	26.44	5.142	6.24	59.8
2	S (%)	0	90.5	22.44	329.63	18.15	1.026	0.716
3	M (%)	1.64	95	43.63	386	19.64	0.043	-0.54
4	C (%)	0	98	32	318.94	17.85	0.92	0.716
5	LL (%)	14.5	495	54.69	2956.9	54.37	5.38	33.49
6	PL (%)	1	119	24.08	94.3	9.71	2.85	18.25
7	PI (%)	1	449	30.74	2547.25	50.47	5.85	38.06
8	OMC (%)	6.8	95	20.49	63.09	7.94	2.65	14.28
9	MDD (kN/m^3)	5.98	23	16.38	4.09	2.02	-0.83	1.85

5. Modeling

Each parameter of G, S, M, C, LL PL, and PI is connected to the OMC and MDD in the preceding Figures in order to develop a direct relationship between these parameters to predict the compaction characteristics from one of these parameters. The Figures and statistical analysis, however, reveal that a reliable direct correlation between the compaction characteristics and the input parameters cannot be accomplished. To resolve this shortcoming and establish a reliable correlation to predict OMC and MDD from input parameters, three models are developed, as shown below, taking into account the influence of soil particle size and index properties.

The models are used to predict the OMC and MDD in this work, and the performance of each model is evaluated using the measured data. To compare the outcomes of the models and measure the performance of each model, the following assessment standards are used: To be considered scientifically accurate and reliable, a model must have a small percentage difference between observed and predicted data, a higher R^2 value, and lower RMSE, Objective (OBJ), MAE, and SI values.

5.1 Multiple Linear Regression Model

The most often used method for estimating the compaction characteristics of soils is the linear regression model (LR) [4, 63, 11, 12], as illustrated in Equation (1):

$$\mathrm{OMC, MDD} = \mathrm{a} + \mathrm{bX} \tag{1}$$

Where a and b are constants, and x might be one of the G, S, F, LL, PL, or PI. The other variables that might affect OMC and MDD, including soil particle - size and soil plasticity, are not included in the previous formulas. To incorporate all the various characteristics and circumstances that could affect OMC and MDD and produce more trustworthy scientific results, the following Equation (2) is proposed.

$$\mathrm{OMC, MDD} = \beta_0 + \beta_1 \mathrm{G} + \beta_2 \mathrm{S} + \beta_3 \mathrm{M} + \beta_4 \mathrm{C} + \beta_5 \mathrm{LL} + \beta_6 \mathrm{PL} + \beta_7 \mathrm{PI} \tag{2}$$

Where G is gravel content (%), S is sand content (%), M is silt content (%), C is clay content (%), LL is the liquid limit, PL is the plastic limit, and PI is the plasticity index.

Moreover, the constant parameters of the model are $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$and β_7. Equation (2) can be viewed as a development of Equation (1) since all variables can be modified linearly. This combination might not always be the case as all factors are unlikely to affect the compaction characteristics and interact with one another. Consequently, frequent updates are required for the model to accurately estimate the OMC and MDD [26, 13, 14].

5.2 M5P-tree Model

Quinlan (1992) invented the M5 algorithm, which later evolved into the M5P-tree algorithm [64]. One of the key benefits of model trees is their ability to effectively solve problems when dealing with multiple datasets with a large number of features and dimensions. They are also well-known for their expertise in dealing with missing data. The M5P-tree method categorizes or divides various data areas into distinct spaces, establishing a linear regression at the terminal node. A multivariate linear regression model demonstrates that it applies to each sub-location. The error is guesstimated by the node's default variance value. The correlations of tree-shaped branches are shown in Figures 5 and 6. Additionally, Equation demonstrates that the generic version of the M5P-tree model equation is

$$\mathrm{OMC, MDD} = \beta_0 + \beta_1(\mathrm{G}) + \beta_2(\mathrm{S}) + \beta_3(\mathrm{M}) + \beta_4(\mathrm{C}) + \beta_5(\mathrm{LL}) + \beta_6(\mathrm{PL}) + \beta_7(\mathrm{PI}) \tag{3}$$

Where G is gravel content (%), S is sand content (%), M is silt content (%), C is clay content (%), LL is the liquid limit, PL is the plastic limit, and PI is the plasticity index. Additionally, $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$and β_7 represent the model parameters.

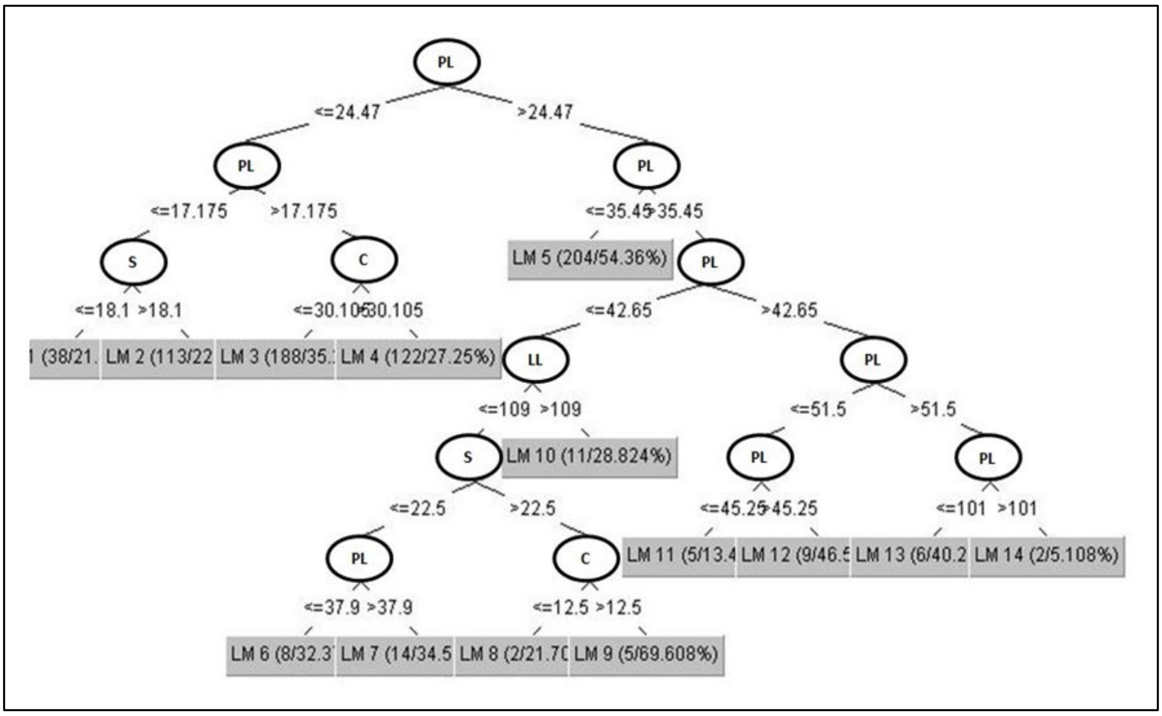

Figure 5: The obtained M5P-tree model for OMC

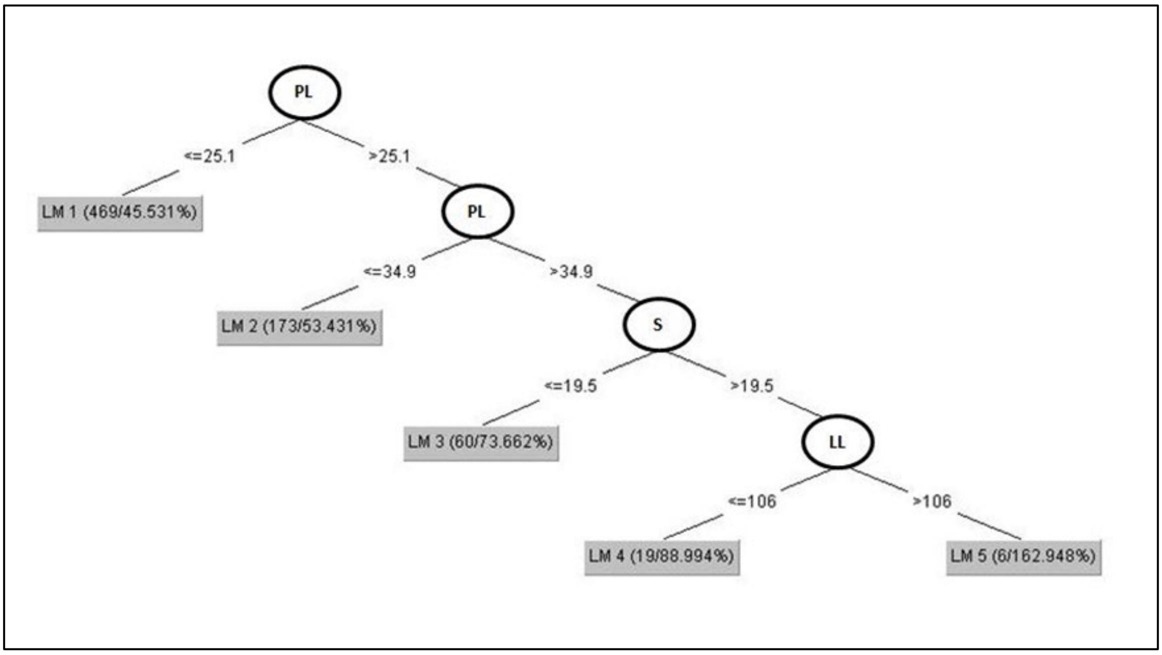

Figure 6: The obtained M5P-tree model for MDD

5.3 ANN Model

Artificial neural networks (ANN) are cognitive computing systems that analyze and simulate nonlinear data using algorithms that only vaguely resemble the operations of the human nervous system [65]. This machine learning method is frequently used in construction engineering to predict the future behaviour of a variety of numerical issues [23, 28]. The ANN model is divided into three layers: input, hidden, and output. Each input and output layer may consist of one or more layers, depending on the intended problem. The hidden layer is frequently extended to include two or more layers. The input and output layers are frequently determined by the designed model's objective and the data collected, whereas the hidden layer is influenced by the rating weight, transfer function, and bias of each layer toward other levels [65].

A multi-layer feed-forward network is built using a combination of proportions, weight/bias, and various parameters, including (G, S, M, C, LL, PL, and PI) as inputs, and the output ANN is either the OMC or MDD. There is no standard approach for designing network architecture. The trial-and-error test is thus harnessed to ascertain the number of hidden layers and neurons. The ultimate focus of the network's training process is to obtain the optimal number of iterations (epochs) from which the minimum mean absolute error (MAE), root mean square error (RMSE), and high R^2-value are obtained. Several studies have been conducted to investigate the effect of iteration on lowering the MAE and RMSE. The obtained dataset (a total of 1038 data) has been split into 2 groups in order to prepare for the designed ANN. Approximately 70% of the datasets were used as trained data to train the network. For the trained network, 30 % data was used for testing. The trained and tested ANN has been used to decide the correct network structure based on the compatibility of the predicted compaction characteristics with the actual obtained data. The ANN structure with one hidden layer, eight neurons, and a hyperbolic tangent transfer function was determined to be the best-trained network that delivers the highest R^2 and the lowest MAE and RMSE for predicting both OMC and MDD (as illustrated in Figure. 9 and Tables 5 and 6). Equations 4, 5, and 6 display the ANN model's General Equation.

From linear node 0:

$$\mathrm{OMC, MDD} = \mathrm{Threshold} + \left(\frac{\mathrm{Node\ 1}}{1+e^{-B1}}\right) + \left(\frac{\mathrm{Node\ 2}}{1+e^{-B2}}\right) + \cdots \tag{4}$$

From sigmoid node 1:

$$\mathrm{B1} = \mathrm{Threshold} + \sum(\mathrm{Attribute} * \mathrm{Variables}) \tag{5}$$

From sigmoid node 2:

$$\mathrm{B2} = \mathrm{Threshold} + \sum(\mathrm{Attribute} * \mathrm{Variables}) \tag{6}$$

6. Model Assessment Tools

Several measures, such as the coefficient of determination (R^2), scatter index (SI), objective (OBJ), root mean squared error (RMSE), and mean absolute error (MAE), were used to assess the proposed models, which may be calculated using the formulas below:

$$R^2 = \left(\frac{\sum_{p=1}^{p}(yi-yi')(yp-yp')}{\sqrt{\left[\sum_{p=1}^{p}(yi-yi')^2\right]\left[\sum_{p=1}^{p}(yp-yp')^2\right]}}\right)^2 \tag{7}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{p=1}^{p}(yp-yi)^2}{p}} \tag{8}$$

$$\mathrm{MAE} = \frac{\sum_{p=1}^{p}|yp-yi|}{p} \tag{9}$$

$$\mathrm{SI} = \frac{\mathrm{RMSE}}{y'} \tag{10}$$

$$\mathrm{OBJ} = \left(\frac{n_{tr}}{n_{all}} * \frac{\mathrm{RMSE}_{tr}+\mathrm{MAE}_{tr}}{R_{tr}^2+1}\right) + \left(\frac{n_{tst}}{n_{all}} * \frac{\mathrm{RMSE}_{tst}+\mathrm{MAE}_{tst}}{R_{tst}^2+1}\right) \tag{11}$$

In the calculations above, yp and yi represent the expected and actual values of the path pattern, respectively, whereas yp' and yi' represent the averages of the actual and predicted values. The terms training and testing datasets are abbreviated as tr and tst, respectively. The term n refers to the number of patterns (collected data) in the related dataset. In contrast to R^2, which has an optimal value of one, the other evaluating factors have optimal values of zero. In terms of the SI parameter, a model performs poorly when it is 0.3, reasonably when it is between 0.2 and 0.3, well when it is between 0.1 and 0.2, and extremely well when it is less than 0.1. The OBJ parameter was also utilized in Equation (11) as an integrated performance indicator to evaluate the efficacy of the suggested models. Positive and negative error margin lines were added to the model findings to visually depict how each model overestimates and underestimates the anticipated effects of OMC and MDD compared to the actual values from the tests. A positive score indicates an exaggerated percentage of OMC and MDD, whereas a negative value indicates an underestimated amount.

7. Results and Analysis

7.1 Predicted and Measured the Compaction Characteristics

7.1.1 The MLR model

Figure 7 describes the correlation between actual and estimated OMC and MDD values for all training and testing datasets. A total of 1038 data sets were utilized to construct the model. In the developed equations, the two plasticity parameters LL and PI significantly contribute to the values of OMC and MDD. The optimal value (a specific value, minimum or maximum) in the equation was unearthed by optimizing the sum of error squares and the least squares method in Excel Solver. In the current model, the weight of each parameter on the OMC and MDD was also determined. The values of other equation cells in the worksheet were used to set limitations or restrictions on this object cell. The following is the Equation for the MLR model with various weight parameters (Equations 12 and 13):

$$\mathrm{OMC} = 15.34 - 0.19\mathrm{G} - 0.166\mathrm{S} - 0.1185\mathrm{M} - 0.05\mathrm{C} + 0.76\mathrm{LL} - 0.065\mathrm{PL} - 0.788\mathrm{PI} \quad (12)$$

$$\mathrm{MDD} = 17.23 + 0.091\mathrm{G} + 0.049\mathrm{S} + 0.029\mathrm{M} + 0.018\mathrm{C} - 0.187\mathrm{LL} + 0.0177\mathrm{PL} + 0.1886\mathrm{PI} (13)$$

According to the above Equations, among other input parameters, PI can have a stronger influence on the decline of OMC and the increase of the MDD value, even though this may contradict experimental findings reported in the literature, which show that a soil with a higher PI has a lower MDD value. The obtained R^2, RMSE, and MAE assessment parameters for the OMC are 0.8, 3.17 %, and 2.51 %, respectively. The MDD, R^2, RMSE, and MAE values are 0.76, 0.95, and 0.75 kN/m^3, respectively. Figures 13 and 14 reveal that the current model's OBJ and SI values for OMC for the training dataset are 3.43 and 0.182, respectively, while these values are 0.97 and 0.057, respectively, for the test dataset.

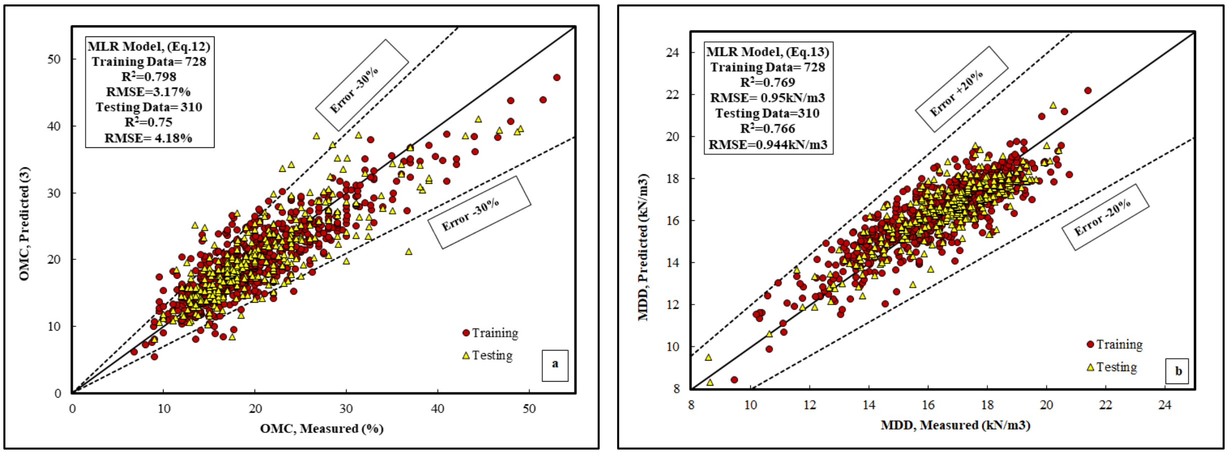

Figure 7: Measured and predicted values of a) OMC and b) MDD for MLR model: training and testing datasets

7.1.2 M5P-tree Model

Figure 8 illustrates the predicted and actual values of both OMC and MDD obtained in the M5P-tree model. Compared to MLR, PL has a relatively greater influence on the compaction characteristics than the other input parameters. Additionally, the model parameters are presented in Tables 3 and 4. The model parameters from the tables are chosen with respect to the linear tree function shown in Figures 5 and 6. In the figures, it is indicated that to predict the OMC, 14 Lum are desired, while there are 5 Lum to predict the MDD. The use of the Lum relies on the input parameters. For example, if the value of PL is 34%, the model equations will be in Lum 5 and Lum 2 for OMC and MDD, respectively, as:

$$\mathrm{OMC} = 19.8 - 0.168(\mathrm{G}) - 0.21(\mathrm{S}) - 0.1(\mathrm{M}) - 0.053(\mathrm{C}) - 0.015(\mathrm{LL}) + 0.535(\mathrm{PL}) - 0.0019(\mathrm{PI}) \quad (14)$$

$$\mathrm{MDD} = 16.73 + 0.0339(\mathrm{G}) + 0.0509(\mathrm{S}) + 0.02(\mathrm{M}) + 0.0187(\mathrm{C}) - 0.14(\mathrm{PL}) - 0.0001(\mathrm{PI}) \quad (15)$$

Table 3: M5P-tree model parameters for OMC

LM	Model Parameters							
	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7
1	1.81	-0.29	-0.01	0.01	0.017	0.201	0.456	-0.03
2	9.836	-0.09	-0.01	0.027	0.053	0.036	0.035	0.025
3	9.3	-0.144	-0.031	-0.002	0.006	-0.026	0.5	-0.019
4	0.006	0.32	0.056	0.11	0.094	-0.043	0.41	0.121
5	19.8	-0.168	-0.21	-0.1	-0.053	-0.015	0.535	-0.002
6	38.9	-0.307	-0.0722	-0.0172	-0.003	0	-0.13	-0.004
7	25.58	-0.3077	-0.0722	-0.0172	-0.003	0	0.243	-0.004
8	28.38	-0.3077	-0.0846	-0.0172	-0.0487	0	0.1696	-0.004
9	27.87	-0.307	-0.084	-0.017	-0.042	0	0.17	-0.004
10	26.85	-0.46	-0.068	-0.017	-0.003	0	0.169	-0.004
11	31.85	-0.266	-0.039	-0.054	-0.003	-0.001	0.196	-0.004
12	15.6	-0.266	0.0376	-0.13	-0.003	-0.0078	0.55	-0.004
13	29.06	-0.266	0.0547	-0.0172	-0.003	0	0.239	-0.004
14	30.8	-0.266	0.0547	-0.0172	-0.003	0	0.196	-0.004

Table 4: M5P-tree model parameters for MDD

LM	Model Parameters							
	β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7
1	21.77	0.0372	0.0015	-0.0173	-0.0245	0	-0.1442	-0.0184
2	16.73	0.0339	0.0509	0.02	0.0187	0	-0.1412	-0.0001
3	14.96	0.132	0.0098	0.0042	0.0031	-0.0009	-0.0569	-0.0001
4	18.035	0.0649	0.0098	0.0042	0.0031	-0.0224	-0.0642	-0.0001
5	20.6	0.065	-0.0984	0.0042	0.0031	-0.0104	-0.0805	-0.0001

As far as OMC is concerned, the obtained R^2, RMSE, and MAE assessment parameters are 0.84, 4.26%, and 2.59%, respectively. For the MDD, R^2, RMSE, and MAE are 0.823, 1.198 kN/m^3 and 0.82 kN/m^{3,} respectively. The OBJ and SI values of the present model for OMC of the training dataset are 3.68 and 0.23, respectively, as shown in Figures 13 and 14, while these values are 1.08 and 0.072 for MDD.

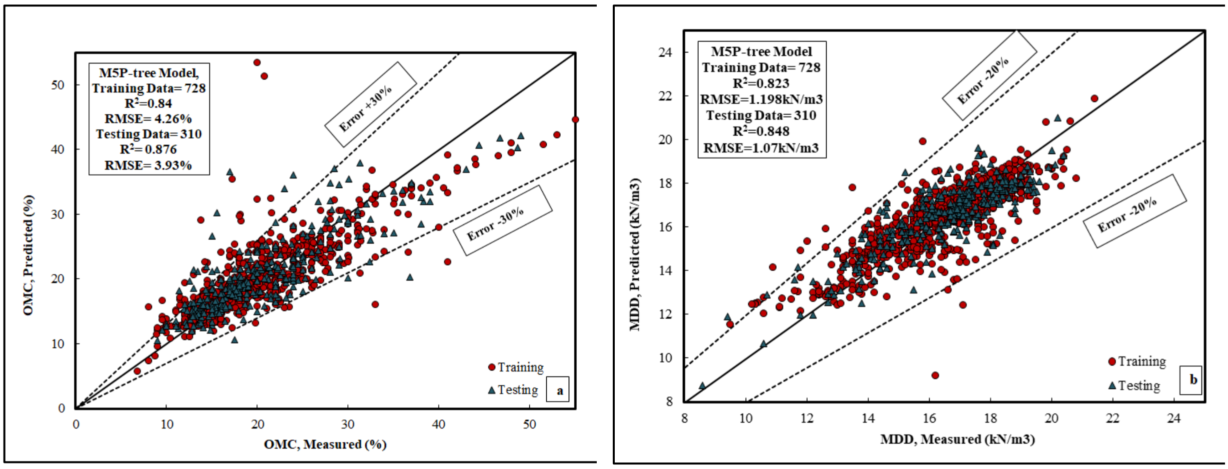

Figure 8: Measured and predicted values of a) OMC and b) MDD for M5P-tree model: training and testing datasets

7.1.3 ANN model

To achieve excellent ANN performance, the author investigated various hidden layers, neurons, momentum, learning rate, and iterations. Tables 5 and 6 display several ANN architectures that were investigated in order to select the optimal ANN model for OMC and MDD. As a direct consequence, it was discovered that an ANN with one hidden layer, eight neurons on the left (as shown in Figure 9), 0.1 momentum, 0.2 learning rate, and 2000 iterations best predict the OMC and MDD. Figure 10 provides a comparative analysis of predicted and actual values of compaction characteristics for both phases (training and testing datasets). The ANN model outperforms other models when estimating the value of OMC. Nonetheless, the ANN model only outperformed the other models in terms of providing R^2 value and predicting MDD. The R^2, RMSE, and MAE assessment parameters for the ANN model are 0.9, 3.41 %, and 2.47 %, respectively, according to the OMC. However, R^2, RMSE, and MAE values for predicting MDD are 0.86, 1.087 kN/m^3, and 0.81 kN/m^3, respectively. Besides this, in the current model, the OBJ for OMC and MDD are 3.05 and 1.0, respectively. Further to that, the SI values for OMC and MDD in the training dataset are 0.184 and 0.06, respectively.

Table 5: the tested ANN architecture for OMC

No. of Hidden layers	No. of Neurons in Hidden Layers			R^2	MAE (%)	RMSE (%)
	The left side	The middle	The right side			
1	6	0	0	0.89	2.7	3.77
1	7	0	0	0.89	2.72	3.78
1	8	0	0	0.909	2.47	3.41
1	10	0	0	0.899	2.55	3.58
2	8	0	6	0.84	2.82	4.36
2	8	0	4	0.836	2.85	4.47
1	12	0	0	0.902	2.43	3.42
1	15	0	0	0.89	2.47	3.54
2	8	0	8	0.84	2.58	4.21
3	6	6	6	0.838	2.77	4.399
3	8	8	8	0.85	2.58	4.13
3	10	10	10	0.849	2.599	4.15

Table 6: the tested ANN architecture for MDD

No. of Hidden layers	No. of Neurons in Hidden Layers			R^2	MAE (kN/m^3)	RMSE (kN/m^3)
	The left side	The middle	The right side			
1	6	0	0	0.829	0.83	1.19
1	8	0	0	0.86	0.81	1.08
1	10	0	0	0.86	0.89	1.17
1	7	0	0	0.849	0.92	1.202
2	8	0	6	0.809	0.868	1.25
3	6	6	6	0.81	0.85	1.23
3	5	5	5	0.8139	0.8513	1.228
3	8	8	8	0.815	0.84	1.225
2	8	0	8	0.8103	0.856	1.24
3	10	10	10	0.8158	0.846	1.23

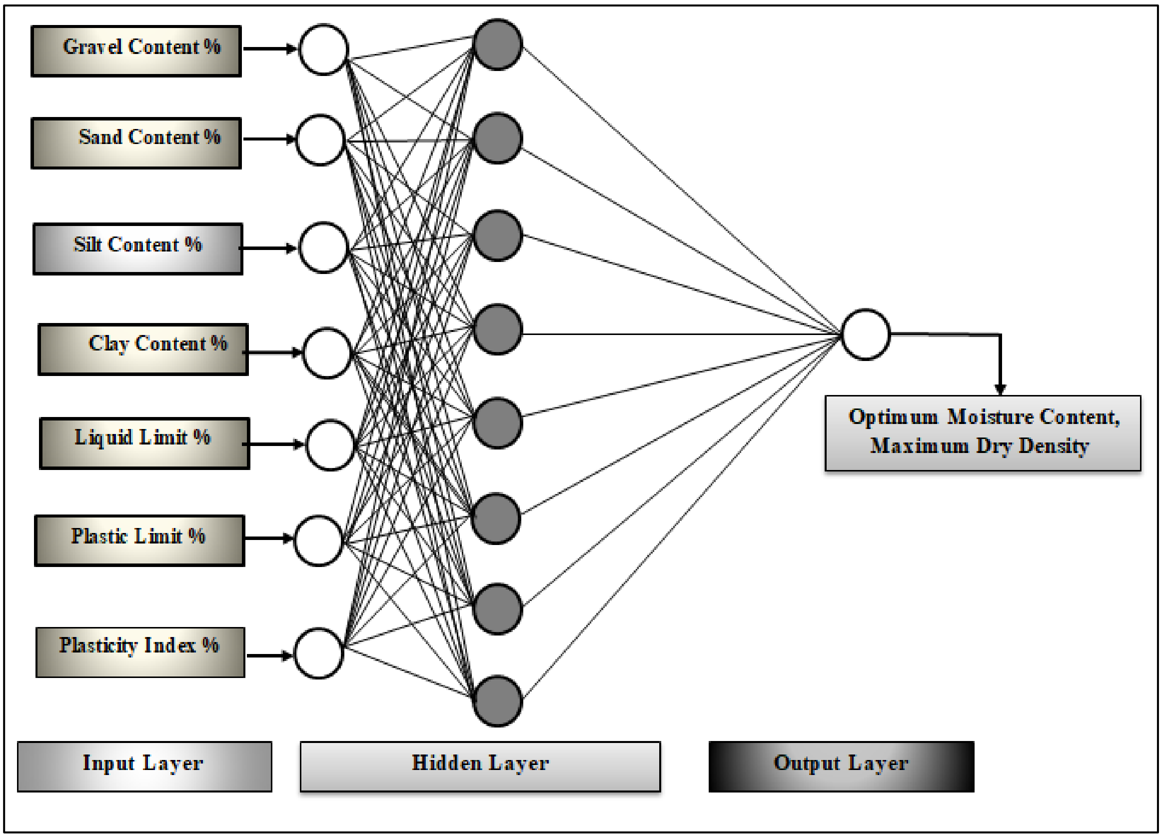

Figure 9: the architecture of the used ANN models to predict both OMC and MDD

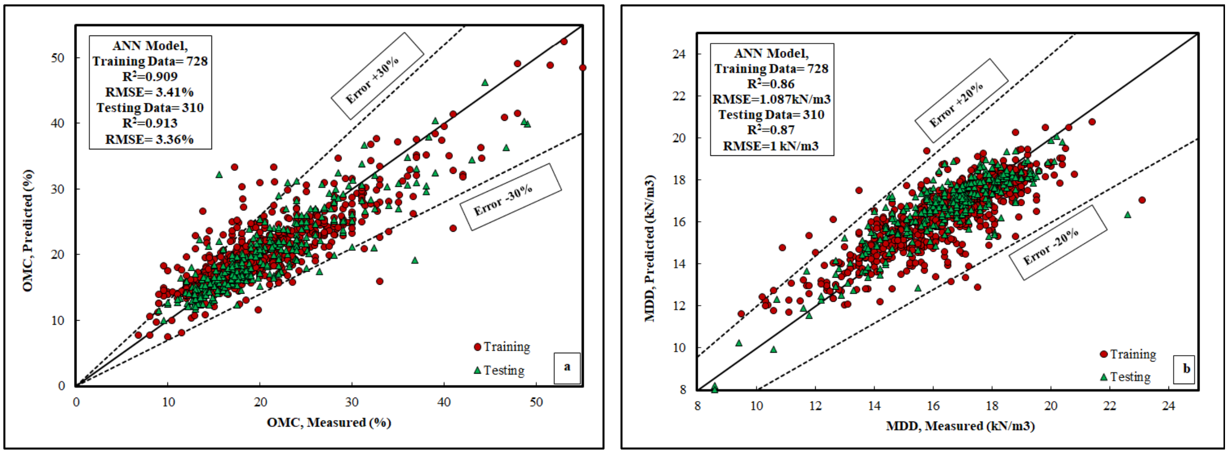

Figure 10: Measured and predicted values of a) OMC and b) MDD for ANN model: training and testing datasets

7.2 Model Comparisons

The potency of the proposed model was classified by employing five different quantitative tools: MAE, R^2, RMSE, OBJ, and SI. R^2, RMSE, and MAE are depicted in Figures 15, 16, and 17.

In terms of OMC, the ANN outperforms the MLR and M5P-tree models in terms of R^2, but the RMSE and MAE values are slightly higher than the MLR model, as shown in Figures 15a, 16a, and 17a, respectively. Figure 12a compares the predicted OMC and the actual measured OMC based on the results of all models. Besides this, Figures 11a and b show the residual error for all models in both phases. Observing actual and predicted OMC values in Figures 11a and 12a reveals that the ANN model outperforms the other models. Figures 13a and b show the OBJ for all of the models.

MLR, M5P-tree, and ANN models have OBJ values of 3.43, 3.68, and 3.05, respectively, to predict OMC (Figure 13a). Despite the fact that the OBJ values for all models are very close, the ANN model has the minimum OBJ value when compared to the others. This indicates that the ANN approach produces more consistent results and is more accurate in predicting OMC.

Figures 14a and 14b display the SI values for the training and testing phases. In Figure 14a, the testing phases for MLR and ANN are between 0.1 and 0.2, indicating satisfactory accuracy. However, the SI value for the M5P-tree model outperforms the fair one. The ANN model performs well in both the training and testing phases. Relying on these analyses, while all models can be used to predict the OMC from physical soil properties to some extent, the ANN model was shown to perform much better.

Regarding MDD, in Figure 14b, ANN still provides better performance than the other models. However, the MLR model provides lower dispersion and percentages of error than other models, as shown in Figures 11b and 12b. Concerning Figure 13b, the OBJ values of MLR, M5P-tree, and ANN are 0.97, 1.08, and 1.0, respectively. MLR model has the least OBJ compared to the other models. In this regard, the MLR and ANN somewhat perform well in predicting MDD. Referring to Figure 14b, the SI value for MLR, M5P-tree, and ANN models are 0.057, 0.072, and 0.06, respectively. These values show that all the models are excellent in predicting MDD. Although all the models are likely to perform well and the ANN model provides higher R^2, MLR performs better in predicting MDD considering all quantitative tools (Figures 15b, 16b and 17b).

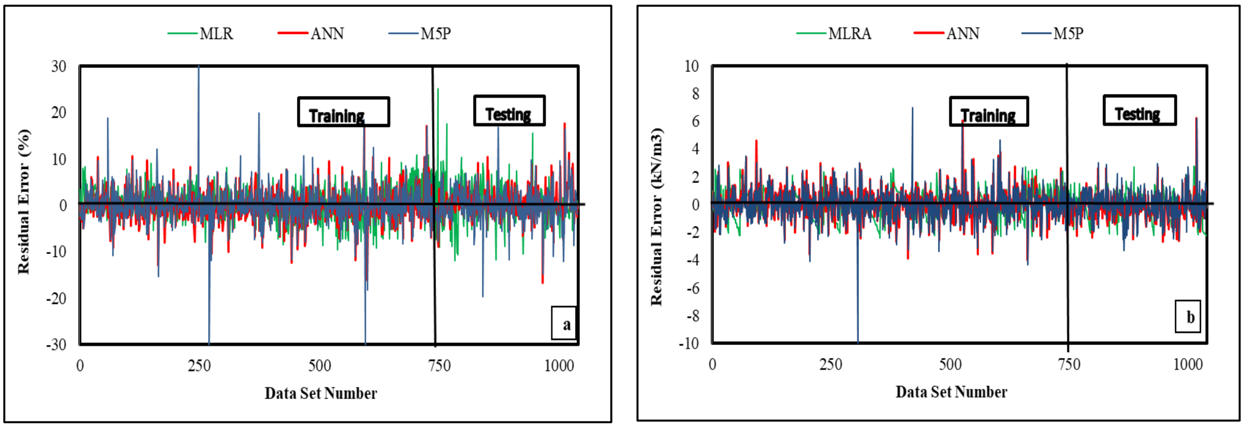

Figure 11: Variation in predicted values of a) OMC and b) MDD based on the four different models

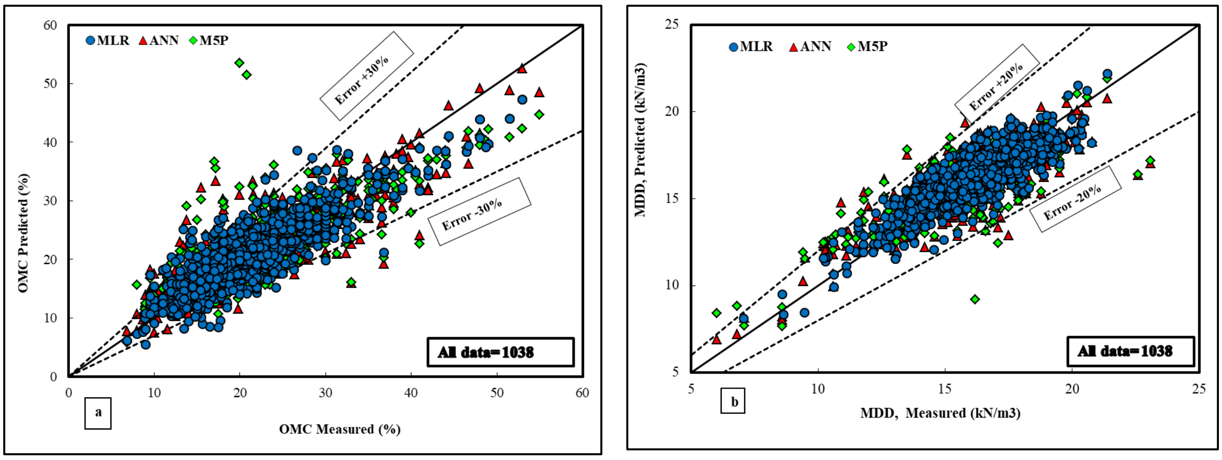

Figure 12: Comparison between model predictions of a) OMC and b) MDD using all data

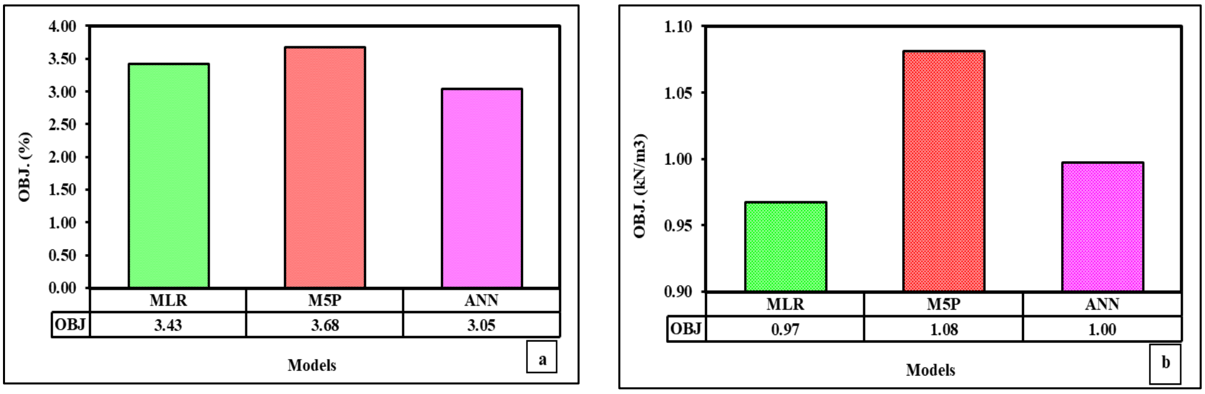

Figure 13: The OBJ values of a) OMC, b) MDD for all the models

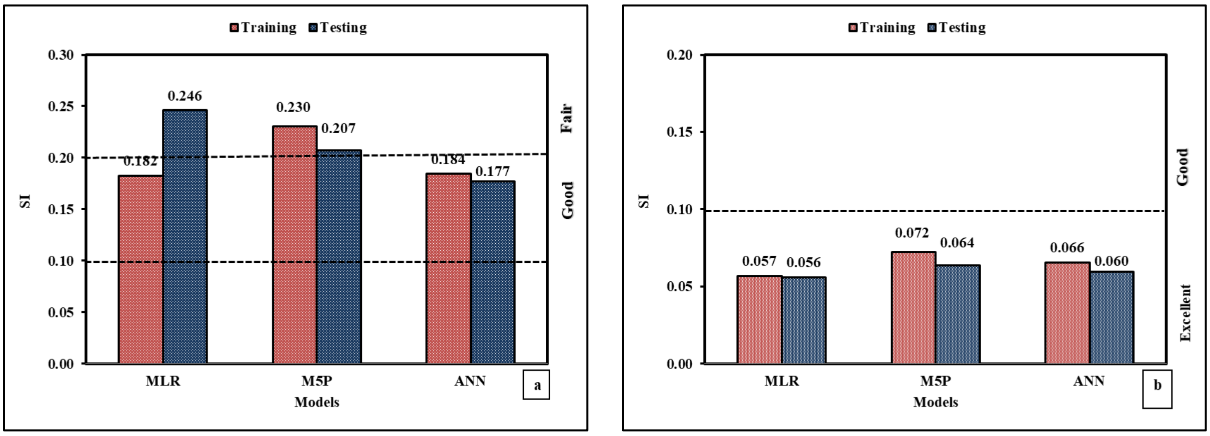

Figure 14: The SI values of a) OMC and b) MDD for all developed models

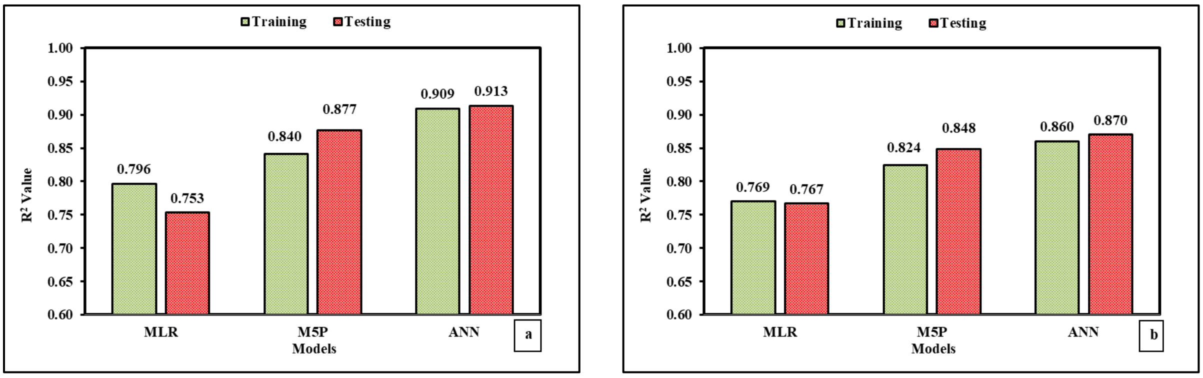

Figure 15: The R^2 values of a) OMC and b) MDD for all four models

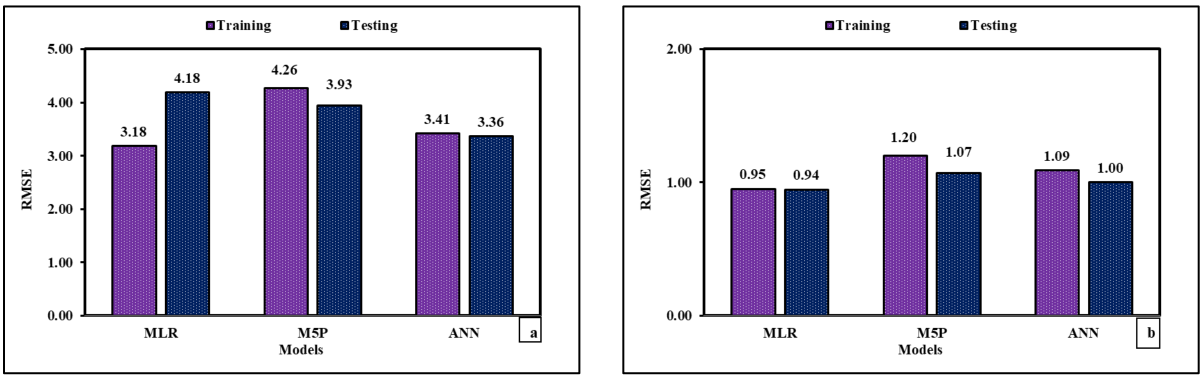

Figure 16: The RMSE values of a) OMC and b) MDD for all four models

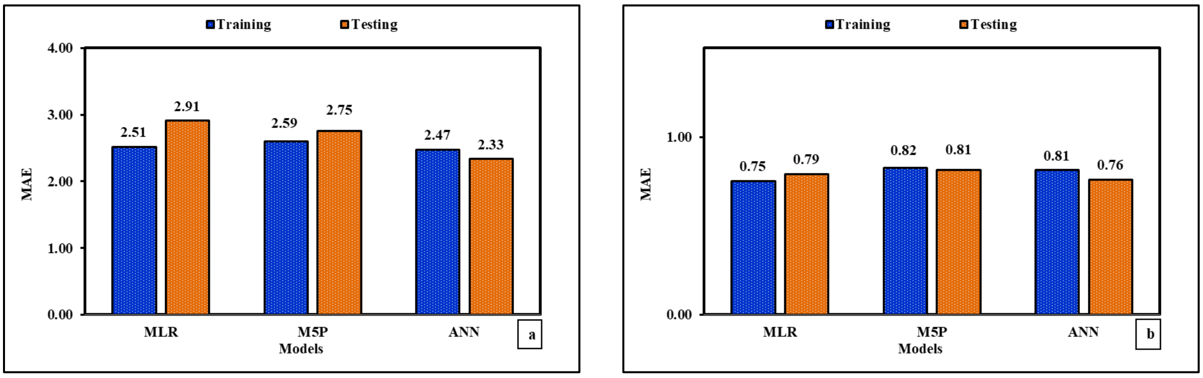

Figure 17: The MAE value of a) OMC and b) MDD for all the four models

7.3 Sensitivity Analysis

Sensitivity analyses were carried out in order to assess the immediate effect of each parameter on the OMC and MDD. The ANN model was chosen for this purpose because it performed the best when compared to the others. In this regard, the true contribution of each parameter in the model to the values of OMC and MDD can be seen. In each of these studies, a single input variable was removed while all training data were combined. To analyze the influence of each parameter, RMSE, R^2, and MAE were calculated separately. Tables 7 and 8 show the differences in statistical tools for predicting OMC and MDD, respectively.

Table 7: sensitivity analysis for ANN model on OMC

No.	Input parameters	Removed parameter	R^2	MAE	RMSE	Ranking
1	G, S, M, C, LL, PL, PI		0.9	4.29	5.14	-
2	S, M, C, LL, PL, PI	G	0.896	4.199	5.058	6
3	G, M, C, LL, PL, PI	S	0.8904	4.54	5.40	5
4	G, S, C, LL, PL, PI	M	0.8909	4.57	5.44	4
5	G, S, M, LL, PL, PI	C	0.89	5.21	6.04	2
6	G, S, M, C, PL, PI	LL	0.8997	3.64	4.55	7
7	G, S, M, C, LL, PI	PL	0.8926	5.24	6.14	1
8	G, S, M, C, LL, PL	PI	0.8925	5.13	5.959	3

Table 8: sensitivity analysis for ANN model on MDD

No.	Input parameters	Removed parameter	R2	MAE	RMSE	Ranking
1	G, S, M, C, LL, PL, PI		0.86	0.81	1.087	-
2	S, M, C, LL, PL, PI	G	0.836	0.834	1.169	6
3	G, M, C, LL, PL, PI	S	0.829	0.9196	1.258	1
4	G, S, C, LL, PL, PI	M	0.828	0.826	1.1935	4
5	G, S, M, LL, PL, PI	C	0.858	0.8128	1.088	7
6	G, S, M, C, PL, PI	LL	0.821	0.8332	1.209	3
7	G, S, M, C, LL, PI	PL	0.829	0.8289	1.187	5
8	G, S, M, C, LL, PL	PI	0.827	0.8778	1.2327	2

When the appraisal values of statistical tools are slightly changed and decreased, the effectiveness of each input parameter is procured. Table 7 illustrates the study's sensitivity analysis consequences for predicting OMC. Although the discrepancy is marginal, it is interesting to see the overall effect of excluding each input parameter on the OMC. The results show that PL is the most influential parameter influencing the value of OMC. When PL is removed from the equation, the R^2 value of the model falls from 0.897 to 0.892. RMSE, on the other hand, increased from 5.14 to 6.14. Table 8 illustrates the impact of a single input parameter on MDD. When S and PI were removed individually, they had nearly the same influence. The R^2 value declined from 0.86 to 0.82; however, the values of RMSE and MAE increased to 1.2 and 0.91 respectively. Therefore, PL can be considered as a parameter with more influence on the value of OMC while, for quantifying MDD, both S and PI play a notable role.

8. Conclusion

It is critical to develop a reliable and accurate model to predict the OMC and MDD for preliminary assessment and to save time when selecting appropriate soils. Since the models' input parameters are soil properties like the percentage of soil particle size and plasticity, they can be resolved utilizing simple laboratory tests. The values of OMC and MDD in the field quantify the properness of compaction. As a result, OMC and MDD can be acquired from such simple properties without the need for standard Proctor tests. This will affect the time required to identify the proper soil for specific earthworks. The outcomes of this work can be summarized based on the analysis and modelling of the 1038 datasets incorporating G, S, M, C, PL, LL, and PI parameters:

- The MLR, M5P-tree, and ANN were established in this study to predict OMC and MDD. In terms of several evaluation tools, the ANN model outperformed the other models, with higher R^2 and lower values of OBJ, RMSE, SI, and MAE, particularly for predicting OMC. Aside from the R^2 value, the MLR model outperforms the ANN and M5P-tree models in predicting MDD.
- The SI values for MLR and ANN models were smaller than 0.2, suggesting good performance in predicting OMC. However, all the models showed excellent performance in predicting MDD.
- For OMC, the OBJ value of the ANN model is slightly smaller than MLR and M5P-tree models. Although the difference is not significant, the ANN model still performs better in predicting OMC. On the contrary, the OBJ value of the MLR model was smaller than both models when predicting MDD.
- Although the R^2 value of the ANN model is higher than other models, MLR and M5P-tree models still have reasonable R^2 values (MLR = 0.8, M5P-tree = 0.84) and can relatively be used as reliable models to predict OMC from G, S, M, C, PL, LL, PI parameters. Similarly, the R^2 value of the MLR model (0.77) and M5P-tree (0.84) can be considered relatively reliable in predicting MDD.
- In the developed equations, PI dominated the MLR model to predict both OMC and MDD. However, in M5P-tree models, PL played a noticeable role compared to the other parameter. This might be attributed to the fact that most of the soil properties utilized in this study were associated with fine-grained soil.
- In order to determine the most influential parameter that impacts OMC and MDD, sensitivity analyses were performed for the ANN model. In light of the analysis, PL is a parameter with more influence on OMC, while MDD is influenced by S and PI.
- Although the ANN model outperforms to predict the OMC and MDD, the MLR and M5P-tree models can be more beneficial in predicting OMC and MDD from the developed equations with respect to the soil's physical properties. This can be attributed to the fact that there is a nature of black box in the ANN approach.

List of Abbreviations

ANN	**The Artificial Neural Network**
OMC	Optimum Moisture Content (%)
MDD	Maximum Dry Density (kN/m^3)
G	Percentage of Gravel (%)
S	Percentage of Sand (%)
M	Percentage of Silt (%)
C	Percentage of Clay (%)
LL	Liquid Limit (%)
PL	Plastic Limit (%)
PI	Plasticity Index (%)
MLR	Multiple Linear Regression
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
OBJ	Objective Value
SI	Scatter Index
R^2	Coefficient of Determination
SP	Standard Proctor
MP	Modified Proctor

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Data availability statement

Not applicable.

Conflicts of interest

The author of the current work does not have a conflict of interest.

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