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ORIGINAL ARTICLE

Comparative Analysis of Random Forest and Artificial Neural Networks for Predicting In-Situ Soil Density

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ABSTRACT

This study suggests that RF and ANN are proven to be robust algorithms in predicting in-situ soil density, which is considered a significant geotechnical parameter. The research is based on 86 soil samples and focuses on five main input parameters: Gravel Percentage (G%), Plastic Limit (PL%), Sand Percentage (S%), Fines Percentage (F%), and Liquid Limit (LL%). The models developed here utilize five commonly recorded index properties (G%, S%, F%, LL, and PL) for all field samples taken from the Basra-Faw Road project. The influence of moisture content and compressive energy was ignored, as all field samples acquired the same moisture content and compressive energy during compression. The fit of the two models was thoroughly tested with statistical indices, including the coefficient of determination (R^2) and Root Mean Square Error (RMSE). The analysis shows that the ANN model has better predictive performance compared to the RF model, with the R^2 and the RMSE equal to 0.98786 and 0.0027 for the ANN model and 0.96249 and 0.0192 for the RF model. This result emphasizes the ANN's great capability in capturing the complicated non-linear relationship between input variables and soil density. Moreover, the study reveals gravel and fines percentages as the most significant parameters that control the prediction of soil density. Results indicated that machine learning methods, namely ANN, can be an easy, quick, and nondestructive alternative to traditional field-testing methods to predict soil compaction. The research findings add to the base of the art in geotechnical engineering by highlighting the benefits of advanced predictive tools in improving soil density revocation accuracy and efficiency. Incorporating other factors, such as moisture content and compressive energy during compaction, into future datasets may enhance the model's generalizability and accuracy. The findings of this study can have significant implications for bidding purposes and safety in infrastructure-related design; the accuracy of the soil density predictions is critical to such applications as foundation design, slope protection, and pavement construction.

Keywords: Random forest (RF), Artificial neural networks (ANN), In-situ soil density, Machine learning, Geotechnical engineering, Predictive modeling

1. Introduction

Field soil density is an important property in geotechnical engineering and represents the mass of compacted soil per unit volume in its natural condition. Field soil density is required in a variety of applications including pavement design, earthwork computation, slope stability assessment, foundation installation, etc., which imposes very high demands on the accuracy of field soil density estimates. They directly affect foundation bearing capacity, slope stability, and the global behavior of geotechnical works. Reliable soil density values used in design cannot be overemphasized when the design of these works is

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at stake [1, 2]. Soil density is an important determinant in the mechanical features and behaviors of a soil under various loadings, and, hence, in geotechnical engineering. It is a primary control on the longevity, strength, and stability of soil-related infrastructure, including roads, bridges, and earth dams. Throughout civil engineering practice, accurate estimation and prediction of soil density is needed at the design and construction stages to ensure structural integrity and performance. How soil density interacts with other important characteristics such as permeability, compressibility, and shear strength helps clarify its importance. Densification techniques such as compaction reduce air voids and enhance unit weight, more effectively increasing the density of the soil to enhance mechanical behavior of the ground. These compaction parameters such as maximum dry unit weight (γdmax) and optimum moisture content (w opt) are often determined through Standard Compaction Tests (SCT) and Modified Compaction Tests (MCT) [3]. Furthermore, sophisticated predictive analytical methods are crucial for assessing soil density without the necessity of extensive laboratory procedures. Recent studies have shown that machine learning techniques can accurately predict soil consolidation parameters using data obtained from nondestructive testing methods [4], highlighting machine learning as a new opportunity in geotechnical engineering by providing accurate predictions with a substantial reduction in costs from traditional testing techniques. Models for predicting soil density have been greatly influenced by the explosion of computational predictive performance and data analytics developed during the past 40 years. Several machine learning algorithms like Artificial Neural Network (ANN), Random Forest (RF) and Gradient Boosting (GB) have been used more frequently for better predictions of soil properties. ANN is attractive due to its ability to model complex nonlinear relationships between input features and outputs. Recent studies found ANN predicts soil compaction characteristics with moderate prediction applicabilities and relatively high determination coefficients (R^2(from index geotechnical properties [5]. Random Forest RF is an ensemble learning approach that increases prediction accuracy by averaging many decision trees, each of which is trained on a different random subset of the data and a random subset of the features [6]. Many geotechnical applications can take advantage of RF's ability to handle high dimensional data and non-linear relationships [7, 8]. In-situ soil density is an integral parameter of geotechnical engineering influencing the design and construction of civil engineering structures. Soil density (often referred to as dry unit weight or bulk density) has a direct impact on other important soil properties including shear strength, compressibility, and permeability [9]. Reliable evaluation of soil density is of fundamental importance in the assessment of compaction level of engineered fills, slope and embankment stability, bearing capacity of foundations and settlement prediction [10]. Poorly compacted soils can suffer excessive settlements and structural damages or even fail catastrophically, so that accurate determination of density is critical for the safe performance and durability of structures. Classic techniques for measuring in situ soil density, e.g., the sand cone test, rubber balloon test, and nuclear densometer test, have been employed for many decades. These techniques can yield relatively accurate estimates in controlled environments; however, they are subject to various limitations. Most of the traditional methods are invasive to some degree, destructive to a certain extent, time and labor consuming, so it is expensive especially in case a high number of tests have to be performed [11]. Besides, precision of determinations with method as nuclear densometer depends on composition of soil, certified operators and rigorous safety measures. Soils are inherently variable, and as such it is generally necessary to carry out many tests. Traditional methods may limit the data from which to draw conclusions regarding the spatial variability of soil density within a site.

The recent development of Machine Learning (ML) in the past decades has provided emerging opportunities to tackle tough problems in different scientific and engineering domains, including geotechnical engineering [12]. The ML algorithms have a potential to learn complex and non-linear relationships among the data without direct programming, which is a significant advantage in modeling complicated geotechnical material behavior [13, 14]. In geotechnical engineering, ML has been employed to address diverse issues, such as predicting soil shear strength, compressibility, pile bearing capacity, landslide susceptibility, and soil classification [13, 14]. Random Forest (RF) and Artificial Neural Networks (ANN) are some examples of the ML method which have been properly applied for regression and classification in various fields.

The models developed here used five commonly recorded index properties (G%, S%, F%, LL, PL) because these were consistently available for all 86 field samples collected from the Basrah-Faw road project. Important in-situ and process variables that also substantially influence field dry density, for example, compaction effort/energy and compaction method, field water content (in-place moisture), sampling depth and layer thickness, degree of saturation, organic content, presence of binders/cementation, and compaction timing/seasonal effects, were not recorded in the available field dataset and therefore were not included as model inputs. This omission reflects the constraints of the field data and implies that model predictions are conditional on the available index properties; practitioners should note this limitation when applying the models to sites where compaction history or moisture conditions differ from those represented.

Literature Review

The involvement of Artificial Neural Networks (ANNs) in geotechnical engineering has a history of several decades, with initial research showing their applicability to solve various complex problems that have arisen [15]. ANNs, which are based on the physical structure and operation of the biological neural systems, are the best means of such tasks as finding correlations between input and output variables that are highly nonlinear [16]. They have also been successfully used to predict possible behaviors of soil for different properties. For example, many researchers have implemented ANNs to forecast the compaction parameters of soils, like maximum dry density (MDD) and optimum moisture content (OMC), based on index properties like Atterberg limits and grain size distribution [28]. The application of ANNs for predicting soil bulk density has been demonstrated with quite acceptable accuracy. [40]. ANNs have also shown versatility in predicting other geotechnical properties, such as the bearing capacity of foundations, liquefaction potential, and slope stability, often surpassing traditional empirical or statistical methods [17]. The advantages of ANNs over traditional methods of learning from data and generalizing to conditions never seen before make them a desirable tool, even though they generally need extensive datasets and finetuning of hyperparameters to curb the risks of overfitting and to secure their strength [18]. Random Forest (RF) is a machine learning algorithm based on the ensemble approach devised by Wang et al, [19] and it is dominantly used in geotechnical cases due to its capacity to predict with high accuracy and to treat high dimensional data without the need for extensive pre-cleaning. RF generates an abundance of decision trees during the training process and the output class is the mode of all the values of the classes (classification) or the mean value of the individual trees' regression respectively. This collection of decision trees is the main reason why the algorithm is less affected by the overfitting that is typical for decision trees and therefore, the predictive performance is also better. RF has been extensively applied in the prediction of soil properties including for example soil organic carbon [17], soil cohesion, and unconfined compressive strength of stabilized soils [20, 21]. Also, RF gives you the relative measure of the explanatory variable importance, which can be very helpful in understanding the influence of the different input parameters on the predicted results [22]. This feature is particularly beneficial when it comes to geotechnical engineering, since it gives the geotechnical engineers a tool for recognizing the peculiar soil parameters that run the specific phenomena. The studies that compared the efficacy of RF and ANN in geotechnical engineering have presented different outcomes, which are mostly subject to the specific issue, database properties, and model execution. Take for instance, Pham et al, [41] claimed that RF was superior to ANN in the determination of the axial bearing capacity of piles. In the same relatable Li et al, [21], in their research on soil database development, concluded that the prediction error from RF regression for various soil properties was generally less than that from ANN. On the contrary, some works of literature have revealed that ANNs achieved superior accuracy, particularly in cases when the data shows a great deal of complexity, and the network structure is properly fine-tuned [23]. In the research of Kamal et al, [24], when assessing landslide susceptibility, reported that RF outperformed ANN in predictive performance (AUC = 0.966) as opposed to ANN (AUC = 0.914), yet a few other articles in the same research field have claimed that ANNs were more precise under particular conditions [25]. In the study by Ahmad et al, [26], the authors compared RF and ANN for energy consumption prediction in buildings highlighting that the more effective model may be chosen based on data features and problem complexity. The inconsistency of the results illustrates the necessity of the problem-specific comparative analysis for the exact selection of the superior ML algorithm. The input parameters considered in this study, Gravel Percentage (G%), Plastic Limit (PL%), Sand Percentage (S%), Fines Percentage (F%), and Liquid Limit (LL%) are fundamental index properties of soils. Grain size distribution (represented by G%, S%, and F%) and Atterberg limits (LL and PL) are routinely determined in geotechnical investigations and are known to significantly influence soil density and compaction characteristics [27]. Soils with higher gravel and sand content generally achieve higher dry densities, while the nature and percentage of fines, along with plasticity characteristics, play a crucial role in determining the packing arrangement and void ratio of the soil matrix. Previous

ML studies predicting soil mechanical properties have frequently incorporated these or similar index properties as inputs [28, 21]. Despite the growing body of research on ML applications in geotechnics, there is a continuous need for studies that specifically compare the efficacy of different algorithms, such as RF and ANN, for predicting in-situ soil density using a common set of easily obtainable soil index properties. Such comparisons are vital for guiding practitioners in selecting the most appropriate tools for rapid and reliable site characterization. Through a detailed comparative study of the Random Forest (RF) and Artificial Neural Network (ANN) models for predicting the in-situ soil density, this research seeks to establish its significance in the area. The work is based on a dataset of 86 soil specimens and the use of five principal geotechnical parameters. The aims are:

1. To create and assess the models of RF and ANN for the prediction of the in-situ soil density based on G%, PL%, S%, F%, and LL%.
2. To contrast the predictive efficiency of the RF and ANN models by the use of standard statistical measures (R^2 and RMSE).
3. To determine the relative weight of the input factors in the prediction of the in-situ soil density.

The outcomes of this study are expected to provide insights on the suitability of RF and ANN for this specific predictive task and to highlight the potential of these ML techniques as efficient, non-destructive alternatives for assessing soil compaction in geotechnical engineering practice. The paper is structured as follows:

Section 2 details the methodology, including data collection and the theoretical background of the employed algorithms. Section 3 presents the comparative analysis of the models and the performance metrics used. Section 4 discusses the results, including model performance and feature importance analysis. Finally, Section 5 offers a discussion of the findings, limitations, and avenues for future research.

2. Methodology

2.1. Data collection

The research employed a comprehensive methodology for gathering soil samples and relevant factors necessary for predicting soil density. The primary dataset originated from the fieldwork projects; 86 samples using a sand funnel machine (sand replacement method) were collected from the Basrah-Faw road project between 2023 and 2024. This dataset includes soil characteristics like bulk density and proportions of sand, silt, and clay. Anomalies were found at the initial stage of model training using data with stringent cross-validation techniques ensuring quality control during the data acquisition process and thus the model accuracy was augmented. This dataset collected is useful for the development of the soil density prediction models that are based on the analysis of several parameters and the parameters are discussed one by one to identify the factors that can help improve the prediction reliability in different terrains and environments. While the only output parameter is the field dry density of granular soil (FDD g/cm^3), the input parameters include gravel (G%), sand (S%), fine content (F%), liquid limit (LL%), and plastic limit (PL%). The data thereby shall be made more understandable through the following summary data of statistics: the minimum, maximum, average and standard deviation values of the samples collected are displayed in Table 1, and a frequency distribution histogram is shown in Fig. 1.The maximum frequency of gravel is between 30 and 40, as shown in Fig. 1(a). According to Fig. 1(b) 1(f), the frequency of S, F, LL, PL, and FDD is highest between 52.5 and 57.5, 9 and 11, 21.75 and 23.25, 20.5-21.5, and 2.05-2.07 g/cm^3, respectively.

2.2. Algorithms employed

In this investigation, two notable algorithms were utilized for estimating soil density. Random Forest (RF) and Artificial Neural Networks (ANN). Both Random Forest and Artificial Neural Networks have demonstrated considerable power. These machine learning algorithms use different properties of the soil to predict the variables, thus, revealing their potential in the area of soil science.

2.2.1. ANN architecture

Artificial neural networks (ANNs) are computer models inspired by the structure and function of human brain biological neural networks. They are the layers composed of artificial neurons, or interconnected nodes, that are responsible for processing information using weight connections in an input layer, one or more hidden layers, and an output layer. The learning procedure of adjusting weights is made by outputting and receiving input data through a sequence of transformations aimed at enhancing prediction accuracy [15, 32].

2.2.1.1. Structure of ANNs. Typically, the construction of an artificial neural network (ANN) consists of three primary layers: the input layer, the hidden layer, and the output layer.

Table 1. Statistical parameters of the collected database.

NO.	Parameters	Units	Types	Minimum	Maximum	Mean	Median	standard division
1	Gravel G	Percentage	Input	2.70	45.80	25.91	26.35	10.25
2	Sand S	Percentage	Input	45.6	91.1	61.63	59.8	9.35
3	Fines F	Percentage	Input	5.8	28.00	12.335	11.00	4.465
4	Liquid Limit LL	Percentage	Input	17.00	35.800	24.042	23.320	4.054
5	Plastic Limit PL	Percentage	Input	12.65	22.62	19.092	19.925	2.509
6	Field dry Density FDD	g/cm^3	Output	1.92	2.1	2.0341	2.04	0.036

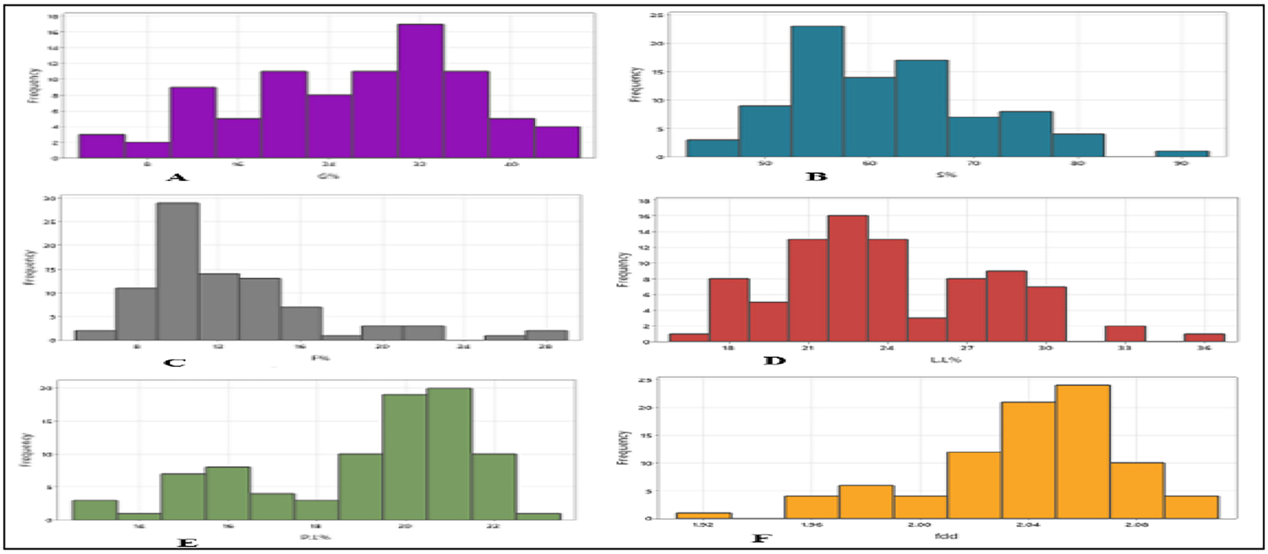

Fig. 1. The graphs (A, B, C, D, E, and F) depict the frequency distribution of the sample's minimum and maximum ranges for gravel (G%), sand (S%), fines (F%), liquid limit (LL%), plastic limit (PL%), and field dry density (FDD).

1. **Input Layer**: The input data is received and dispatched to the hidden layers. Every neuron of this layer is matched to a feature in the input data [33]. This study led to the analysis of five input features. the percentages of gravel (G%), sand (S%), fine material (F%), liquid limit (LL%), and plastic limit (PL%).
2. **Hidden Layers:** The layers are the components that are engaged in the input data processing, transformation as well as computation. Their configuration can be different but is typically between one and several depending on the difficulty of the task [34]. The number of neurons in the hidden layer was established through the experiments carried out with a variation of 5 to 30 neurons and the performance which was assessed by using a validation set.
3. **Output Layer:** The last layer in the neural network that produces the final result (this can be either a regression or classification solution depending upon processed inputs) is called the output layer according to [35]. The output layer in this study was configured as a single neuron, representing the expected field dry density (FDD).

2.2.1.2. Activation Functions. The level of activation functions in neural networks has a serious effect on performance, especially in the hidden and output areas. The rectified linear unit (ReLU) is preferred in hidden layers due to its operational efficiency as well as its potential to eliminate the vanishing gradient problem that commonly occurs in functions like sigmoid and tanh [36]. The linear activation function perfectly fits the need for regression output layers as it directly predicts continuous values without any transformations [37].

2.2.2. RF architecture

Random Forest (RF) is a flexible technique for machine learning, and it is typically employed in classification and regression issues. The algorithm links with the help of many decision trees to the prediction outputs of an object to get more precise results and better resilience. The performance of the algorithm can significantly improve with the parallel processing on the platforms like the field-programmable gate arrays [29]. Besides, the RF method is also the most preferred one in the analysis of importance feature enabling the researchers to reveal the important variables affecting the predictions [30].

However, largescale applications face model size problems, which leads to the need for approximation strategies to sustain costs without compromising correctness [31]. Additionally, improvements like the M-ary Random Forest (MaRF) enhance the method by introducing multi-feature splits, which, in turn, boost performance on different datasets. The RF model, it should be noted, is that overfitting especially in small datasets may result due to too much complexity. Due to the competing directions of tree depth and number, which together affect the model generalization and accuracy, both need to be carefully handled throughout the process. In the current study, the number of trees included was 75, 100, 125, 150, 200, 300, and 400 respectively. The conventional analyses of these two methods versus the variable conditions such as inherent methods of machine learning (ML) and others say that, while ANNs are really good to detect complex patterns in data once they get the proper training, the user-friendliness and toughness of RF are together the substantial reasons why it does a good job even in situations where other methods do not. Consequently, the mixed use of these two techniques into the forecasting models can, in fact, be the choice of their strengths and together are capable of enhancing soil density estimations even more.

3. Comparative analysis of models

3.1. Performance metrics used for comparison

Various indices are employed to compare predictive models in terms of soil density in the soil layer to provide a comprehensive measurement of their performance.

The coefficient of determination (R)

Formula: $R = 1 - (SS_{res} / SS_{tot})$

Where SS_{res} is the sum of squares of residuals (the difference between actual and predicted values). SS_{tot} is the total sum of squares (the difference between actual values and the mean of the actual values).

The Root Mean Square Error (RMSE)

$$\text{Formula:} \quad \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (E_i - P_i)^2}{N}},$$

Where N is the number of experimental datasets, Ei is the experimental value of the FDD at the ith level, E is the mean of the experimental values, Pi is the predicted value of FDD of concrete values at the ith level.

Soil density predictive models that are built with the knowledge of geotechnical applications will need to be equipped with an understanding of performance indicators like R and RMSE. With the help of both explanatory power and error rates, researchers can choose the best models for potential real-life application after overcoming the variations and errors existing in the geotechnical data.

4. Results and analysis

The comparison of Random Forest (RF) and Artificial Neural Network (ANN) algorithms in terms of predicting in-situ soil density was done using different statistical metrics. This part of the text provides a detailed overview of the functional parameters of both models, the ability to predict, and the effect of the input characteristics on the soil density prediction.

4.1. Model performance comparison

The dataset of 86 soil samples was used to build both RF and ANN models, where 80% of the samples were used to train while 20% were utilized for testing. The models' performance was evaluated with three parameters: coefficient of determination (R^2), Mean Square Error (MSE), and Root Mean Square Error (RMSE).

4.1.1. Artificial neural network (ANN) model

The optimal structure of the ANN model was identified by configuring it with various architectures and changing the number of neurons in the hidden layer from 5 to 30. The performance metrics of the ANN model with different configurations are given in Table 2. Results showed that ANN model with 11 neurons in the hidden layer was the best model for testing data set with R^2 value of 0.98786 and RMSE of 0.0066 g/cm^3. This configuration performed also very well for whole dataset with RMSE = 0.0027 g/cm^3. The architecture of the optimal ANN model is illustrated in Fig. 2, which shows the input layer with five parameters (G%, S%, F%, LL%, PL%), a hidden layer with 11 neurons, and an output layer predicting in-situ soil density.

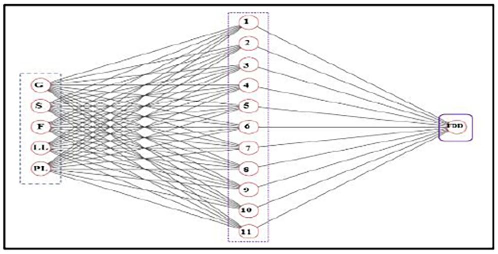

Fig. 2. Architecture of the optimal ANN model with 11 neurons in the hidden layer.

Table 2. Performance metrics for ANN models with varying number of neurons in hidden layer.

NO	No of Neural in hidden layer	R-train	Mes	RMSE	R-test	Mes	RMSE	R-all	Mes	RMSE
1	5	0.96524	1.4588e-06	0.0012	0.97861	3.0696e-05	0.0055	0.96813	1.3811e-06	0.0012
2	7	0.96257	1.6846e-04	0.0130	0.96769	3.0205e-04	0.0174	0.96356	2.4739e-04	0.0157
3	9	0.97179	1.7732e-06	0.0013	0.97925	2.5853e-07	5.0846e-04	0.97273	4.8036e-05	0.0069
4	11	0.96719	1.0141e-06	0.0010	0.98786	4.2941e-05	0.0066	0.97152	7.5411e-06	0.0027
5	13	0.96815	1.7964e-05	0.0042	0.96884	1.1541e-06	0.0011	0.96833	7.2874e-06	0.0027
6	15	0.96992	6.9274e-06	0.0026	0.9826	6.2171e-06	0.0025	0.97271	3.4370e-05	0.0059
7	17	0.96186	9.3673e-07	9.678e-4	0.94385	6.3000e-09	7.9373e-05	0.95871	1.2828e-06	0.0011
8	19	0.9661	1.4331e-06	0.0012	0.93184	2.5048e-04	0.0158	0.95913	2.0479e-05	0.0045
9	21	0.94838	5.6808e-05	0.0075	0.89492	7.1575e-05	0.0085	0.93296	9.7131e-07	9.8555e-04
10	23	0.997161	5.6439e-06	0.0024	0.95788	9.9861e-05	0.0100	0.96919	5.0961e-07	7.1387e-04
11	25	0.94705	1.5436e-04	0.0124	0.89732	8.7252e-07	9.3409e-04	0.93303	4.6138e-05	0.0068
12	27	0.97522	7.4494e-06	0.0027	0.91163	1.2561e-05	0.0035	0.95987	3.7531e-05	0.0061
13	29	0.97013	1.2232e-04	0.0111	0.76282	1.3515e-04	0.0116	0.92008	1.2163e-07	3.4875e-04
14	30	0.93725	2.4444e-08	1.5635e-4	0.85802	2.6144e-04	0.0162	0.9122	6.0241e-04	0.0245

Table 3. Performance metrics for RF models with varying number of trees.

No	Number of trees	R-train	MSE (train)	RMSE (train)	R-test	MSE (test)	RMSE (test)	R-all	MSE (all)	RMSE (all)
1	75	0.96414	2.1211e-05	0.0046	0.95192	4.0436e-04	0.0201	0.95969	2.5323e-06	0.0016
2	100	0.96437	2.7735e-05	0.0053	0.95437	4.2321e-04	0.0206	0.96071	6.9441e-06	0.0026
3	125	0.96371	2.7004e-05	0.0052	0.95568	4.2274e-04	0.0206	0.96054	6.6245e-06	0.0026
4	150	0.96468	2.7873e-05	0.0053	0.95908	4.0257e-04	0.0201	0.96197	6.7645e-06	0.0026
5	200	0.96477	3.0207e-05	0.0055	0.96138	3.8974e-04	0.0197	0.96226	7.9230e-06	0.0028
6	300	0.96671	2.2148e-05	0.0047	0.96249	3.6982e-04	0.0192	0.96421	8.9425e-06	0.0030
7	400	0.96496	2.0220e-05	0.0045	0.95817	3.9514e-04	0.0199	0.96193	9.9602e-06	0.0032

4.1.2. Random forest (RF) model

The RF model was evaluated using different numbers of decision trees (ranging from 75 to 400) to determine the optimal configuration. Table 3 presents the performance metrics of the RF model with varying number of trees.

The RF model with 200 trees exhibited the optimal performance for the testing dataset with an R^2 value of 0.96138 and RMSE of 0.0197 g/cm^3. However, the RF model with 300 trees showed the highest overall R^2 value of 0.96249.

4.2. Comparison between ANN and RF models

To objectively compare the performance of both models, the optimal configurations (ANN with 11 neurons and RF with 300 trees) were selected. Fig. 3 illustrates the comparison between measured and predicted in-situ soil density values for both models.

This figure clearly illustrates the superior performance of the ANN model (subplot A) compared to the RF model (subplot B) in predicting in-situ soil density values. Key observations from the figure:

1. **ANN Model (subplot A):**
   - Shows excellent agreement between measured and predicted values.
   - Data points cluster tightly around the perfect prediction line (y=x).
   - Has a high coefficient of determination ($R^2 = 0.98786$).
   - Demonstrates a very low root mean square error (RMSE = 0.0066 g/cm^3).
   - Most data points fall within the ±5% error bands.
2. **RF Model (subplot B):**
   - Shows good but less precise agreement between measured and predicted values
   - Has more scatter around the perfect prediction line.
   - Exhibits a lower coefficient of determination ($R^2 = 0.96249$).
   - Has a higher root mean square error (RMSE = 0.0192g/cm^3).
   - More data points fall outside the ±5% error bands.

The distinction between training (blue circles) and testing (red triangles) data points provides additional insight into the models' generalization abilities. The ANN model maintains consistent accuracy across both training and testing datasets, while the RF model shows more variability, particularly in the testing set. This visualization effectively supports the conclusion

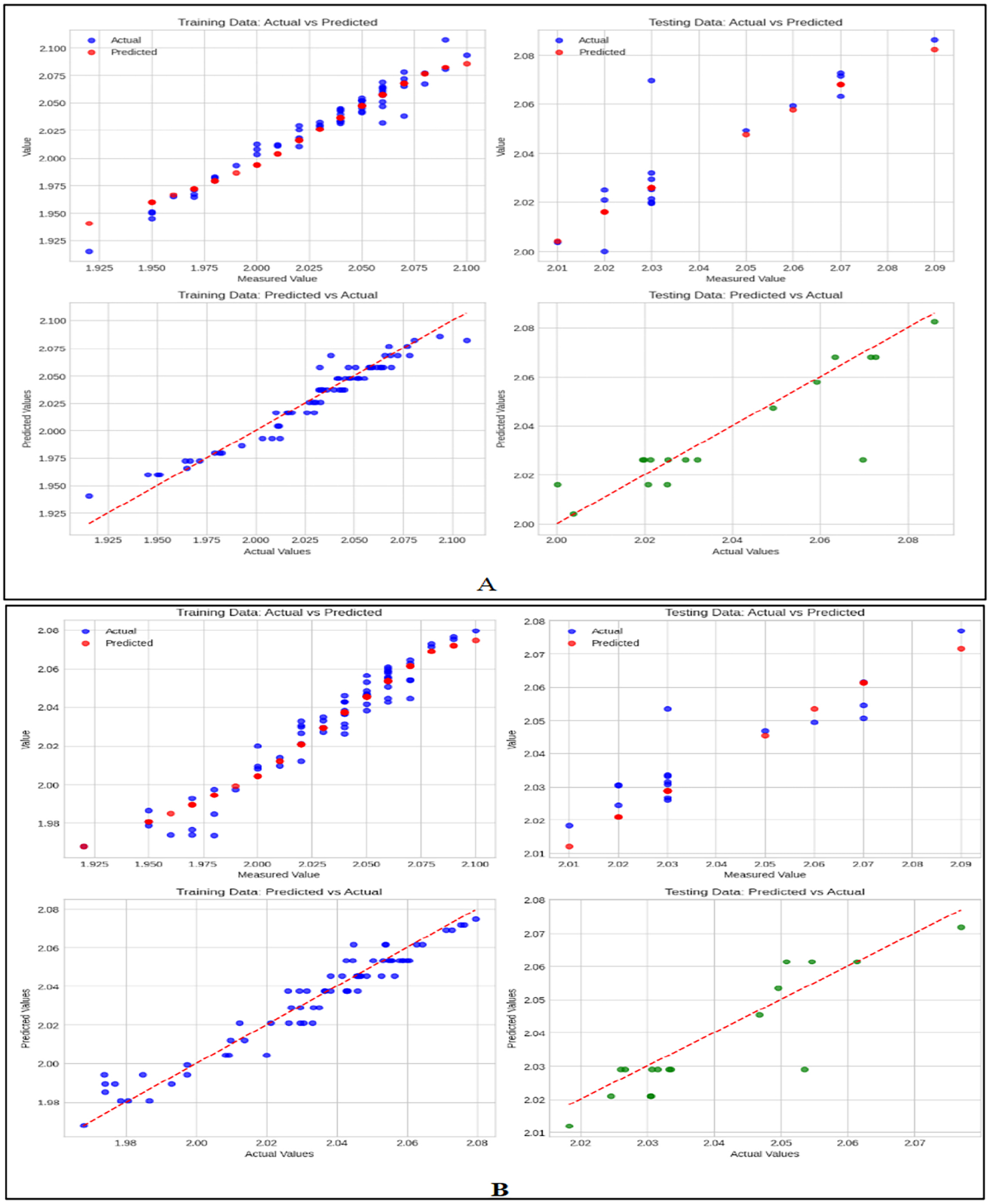

Fig. 3. Comparison between measured and predicted in-situ soil density values: (A) ANN model and (B) RF model.

that the ANN model significantly outperforms the RF model in predicting in-situ soil density, making it the preferred choice for geotechnical applications requiring accurate soil density estimation. Comparison shows that ANN model is better than RF model for predicting in-situ soil density. R^2 of 0.98786 and RMSE of 0.0066 g/cm^3 for the testing dataset for the ANN model, and R^2 of 0.96249 and RMSE of 0.0192 g/cm^3 for the RF model. This is an enhancement of around 2.7% in R and a reduction in RMSE of 66.5% compared to the RF model applied. For the complete data set, the ANN model still performed better (RMSE = 0.0027 g cm^3) than the RF model (RMSE = 0.0028 g cm^3). The smaller values of error indices, as well as the higher value of coefficient of determination, show more accurate and precise of the ANN model estimation for in-situ soil density under various soil conditions.

4.3. Feature importance analysis

Before presenting the results of the quantitative feature significance analysis, it is explicitly

Table 4. Feature importance analysis for ANN model.

No.	Neurons in hidden layer	Importance of G%	Importance of S%	Importance of F%	Importance of LL%	Importance of PL%
1	5	0.127	0.346	1.000	0.088	0.120
2	7	1.000	0.329	0.488	0.054	0.129
3	9	1.000	0.156	0.697	0.109	0.283
4	11	1.000	0.202	0.169	0.004	0.092
5	13	1.000	0.221	0.373	0.043	0.167

Table 5. Predictor importance estimates for RF model.

No.	Number of trees	Importance of G%	Importance of S%	Importance of F%	Importance of LL%	Importance of PL%
1	75	16.47	12.21	19.39	11.28	15.64
2	100	22.67	15.31	24.62	15.76	20.64
3	125	27.65	19.52	31.55	19.88	25.40
4	150	33.88	23.45	38.27	23.42	29.98
5	200	46.10	30.71	51.13	29.80	40.27
6	300	69.73	45.70	97.93	43.32	58.33
7	400	43.80	61.95	104.20	59.15	77.85

acknowledged that several potentially influential parameters were not available in the Basra-Faw field dataset and were therefore not included in model training or significance analysis. The dataset (86 samples) consistently recorded five index characteristics: gravel percentage (G%), sand percentage (S%), fine material percentage (F%), liquid limit (LL), plastic limit (PL), and measured field dryness density (FDD). The influence of moisture content and compaction energy was ignored, as all field samples gained the same moisture content and compaction energy during compaction. Consequently, these could not be used as inputs. These variables include, in particular, compaction effort/energy (compacting method and equipment) and in situ water content (field moisture at the time of compaction). Other unrecorded parameters that may also influence FDD include sampling depth, layer thickness, degree of saturation, organic content, presence of stabilizers/binding materials or cement, and temporal/seasonal compaction effects.

4.3.1. Feature importance in ANN model

The feature importance analysis for the ANN model was conducted by examining the connection weights between the input layer and the hidden layer. Table 4 presents the normalized importance coefficients for each input parameter in the ANN model with different numbers of neurons in the hidden layer.

For the optimal ANN model with 11 neurons in the hidden layer, Gravel Percentage (G%) exhibited the highest importance with a normalized coefficient of 1.000, followed by Sand Percentage (S%) with 0.202, Fines Percentage (F%) with 0.169, Plastic Limit (PL%) with 0.092, and Liquid Limit (LL%) with the lowest importance of 0.004.

4.3.2. Feature importance in RF model

The RF model's feature importance was assessed using predictor importance estimates derived from the out-of-bag permutation technique. Table 5 presents the importance estimates for each input parameter with different numbers of trees.

For the optimal RF model with 300 trees, Fines Percentage (F%) demonstrated the highest importance with a value of 97.93, followed by Gravel Percentage (G%) with 69.73, Plastic Limit (PL%) with 58.33, Sand Percentage (S%) with 45.70, and Liquid Limit (LL%) with 43.32. Fig. 4 illustrates the comparison of feature importance between the optimal ANN and RF models, highlighting the different ranking of input parameters by each model.

5. Discussion

The results presented in the previous section show that the Artificial Neural Network (ANN) model outperforms the Random Forest (RF) model in predicting in-situ soil density using the given dataset of 86 soil samples and five input features (gravel percentage, plastic limit, sand percentage, fines percentage, and liquid limit). With an R^2 of 0.98786 and RMSE of 0.0027, the ANN model performed better than the RF model, which had an R^2 of 0.96249 and RMSE of 0.0192.

This section will expound on the findings, compare them to current literature, discuss practical implications, point out the study's limitations, and give suggestions for future research. The ANN outperformance in this particular case suggests that the between the specifically selected soil index properties and in-situ soil density characteristics might

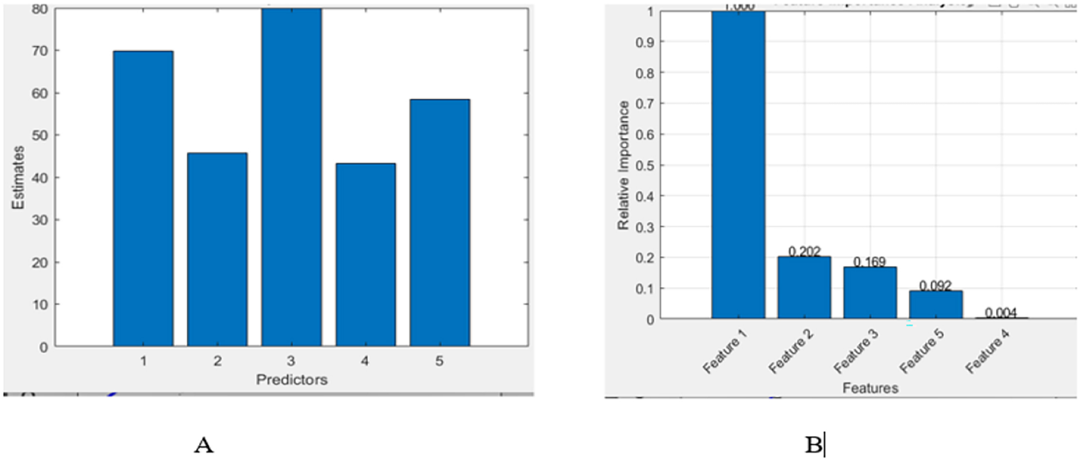

Fig. 4. Feature importance comparison: (A) RF model and (B) ANN model.

have complicated connections or high incidence of non-linearity which the ANN could capture more effectively compared to RF model therefore its non-linear architecture and non-linear activation functions. ANNs can, in certain cases, more accurately approximate extremely complicated functions if they are properly constructed and trained, even though RF can also simulate nonlinearities [3]. In the meantime, the average of the ANN's predictions which were significantly lower showed that its RMSE was excellent in reality the actual measured soil densities were positioned much closer to the ANN. For geotechnical predictions, this degree of precision (R^2 reaching 0.99) is quite remarkable given that material variability is typically present. The result that ANN surpassed RF is quite interesting automatic because, as per the majority of geotechnical studies, at the point when feature interactions are more tree-like or with fewer datasets, RF is prefabricated more accurate or resilient [38, 21]. In a case of volcanic island construction, [21] the authors found that the Random Forest mostly made less prediction errors than Artificial Neural Networks did. On the other hand, numerous comparisons have demonstrated the superiority of ANNs, which is consistent with the findings of the present study [23]. This leads to the conclusion that there is no such thing as a single "best" machine learning technique; rather, the performance variability is due to a multitude of factors including the details of the dataset, the problem, the input features selected, and the level of model modification. The comparative analysis of RF and ANN models for predicting in-situ soil density yields several important insights:

1. Model Performance: The ANN model tends to outperform the RF model in terms of all performance measurements with the best ANN structure (11 number of neurons) achieving an R^2 value of 0.97152 and an RMSE of 0.0027 g/cm^3, compared to the R^2 value of 0.96421 and RMSE of 0.0030 g/cm3 obtained with the RF model. This significant improvement in predictive performance is due to the ANN's capacity to model complex non-linear interactions between the input variables and the soil density.
2. Feature Importance: Both models ranked Gravel Percentage (G%) and Fines Percentage (F%) as the most important predictor in determining the in-situ soil density but with reference to ranking these predictors. This is consistent with the geotechnical knowledge that the particle size distribution pattern largely impacts on the soil compaction response and density obtained.
3. Computational Efficiency: Although acceptable prediction can be obtained by both models, the prediction performance of ANN is better with a smaller number of neurons in only a hidden layer (11 neurons), which is computationally efficient in the context of practical use.
4. Practical Implications: The proposed models, and specifically the ANN model, provide an expeditious and non-destructive alternative to common field tests to evaluate soil compaction. This will greatly cut the time and cost for geo-technical exploration and have the higher predictability. This is in accordance with those reported by Pant et al. [52]. ML models can accomplish a noninvasive test without disturbing the soil sample, and can fill repeated measurements without deterioration. The results indicate that the ANN model is a highly technical approach for forecasting in place soil density with the help of the physical characteristics of soil that are easily tested, besides this it provides great support in geotechnical engineering

applications like construction quality control, embankment design, and foundation analysis.

6. Conclusions

This study examined the implementation of machine learning techniques, particularly Random Forest (RF) and Artificial Neural Network (ANN), for predicting soil in-situ density based on various soil physical properties. After in-depth analysis and assessment of the performance of both models, the conclusions that could be reached are as follows:

1. The ANN model was able to outperform the RF model in terms of predictive performance for in-situ soil density estimation. ANN model achieved the highest R^2 value of 0.98786 and a lower RMSE of 0.0066 g/cm^3 for the testing dataset with the optimal architecture of 11 neurons in the hidden layer. This significantly exceeds the RF model's performance with R^2 of 0.96249 and RMSE of 0.0192 g/cm^3 for 300 trees.
2. Feature importance analysis revealed that Gravel Percentage (G%) and Fines Percentage (F%) were the most influential factors affecting in-situ soil density prediction in both models, though their relative importance differed between models. In the optimal ANN model, G% showed the highest normalized importance coefficient of 1.000, while in the RF model, F% demonstrated the highest importance with a value of 97.93.
3. The sensitivity analysis demonstrated that both models exhibit similar trends in response to parameter variations, with the ANN model capturing more nuanced relationships, particularly at intermediate values of input parameters.
4. Model performance evaluation across various configurations revealed that increasing the complexity of the RF model beyond 300 trees or the ANN model beyond 11 neurons in the hidden layer did not yield significant improvements in predictive accuracy, suggesting that these optimal configurations balance model complexity and performance.
5. The ANN model built is an advanced, rapid, and non-destructive substitute for the conventional field techniques for the accurate estimation of in-situ soil density, widely used thus saves the time and cost of geotechnical investigations.
6. The results of this research emphasize that Artificial Neural Networks (ANNs) the machine learning method of choice is a valid technique in the modeling of the intricate nonlinear interplay between dust physical deformation and density thus, are seen as powerful instruments for their use in geotechnics. The results of the research show that the ANN technique is efficient and reliable for estimating in-situ soil density on the basis of the soil's easily measurable properties.

Moreover, it can be utilized in geotechnical engineering operations for effective soil compaction assessment, quality control processes, and foundation design application The next study is expected to expand the model's usage by covering a broad range of soil types and other environmental conditions and it should include other parameters in order to achieve better results as well.

A major limitation of this study is that the field dataset used for model training and testing contained only the five soil index properties (G%, S%, F%, LL, PL) and did not include several other influential variables because they were not recorded during field testing. The omitted variables consist of compaction effort/energy, compaction method, in-place water content (field moisture), sampling depth, layer thickness, degree of saturation, organic content, and any stabilizers or binders that may be present. As such, the models predict field dry density conditional on the measured index properties; incorporating the omitted variables in future datasets and models is expected to improve accuracy and generalizability. We therefore recommend that subsequent field campaigns record compaction history and moisture conditions (at minimum) and that future model comparisons include these variables where available.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflict of interest

The authors declare no conflict of interest.

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Author contribution

The authors' contributions are as follows.

Eng. Jinan Ali Abd Al-Kareem AL-Maliki: Conceptualization, Methodology, Data Collection, Writing - Original Draft.

Dr Ammar Salman Dawood: Supervision, Validation, Review & Editing.

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