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Application of Deep Neural Networks in Geo-Environmental Engineering

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Abstract

Overcoming the negative effects of unrecyclable materials has become a global concern in the last ten years. One of the unrecyclable materials used to make containers is polyethylene-terephthalate (PT). The use of such materials in enhancing soil has grown in significance. A tree-based classification method for the increase in shear strength brought on by PT elements was developed in this study. Two models were created to forecast shear strength as a result of a series of parametric studies. These parametric research sought to identify the most effective hyperparameters for tree-based models. Based on empirical investigations, the DT and RF models were created to forecast shear strength. These numerical simulations specifically looked for the best model parameters for tree-based models. When comparing the performance of the DT and RF models, the RF model performed better with R^2train=0.95 and R^2test=0.87. As a result, upon the other indices, the RF model appears to be the most reliable in terms of prediction.

1. Introduction

Unrecyclable materials are now a major problem on a global scale since the previous ten years. Polyethylene-terephthalate is primarily used to create plastic containers (PT). The usage of such products has greatly increased the importance of soil improvement. According to studies (Peddaiah et al., Necmi and Ekrem, and Consoli et al., 2020), using PT elements as reinforcements for loose soils can decrease the negative environmental effects of these components, bring down the cost of surface treatment projects, and raise the shear strength of the soil. Polyethylene terephthalate is the most widely used thermoplastic polymer resin from the polyester family and is used in garment fibers, fluid and culinary containers, thermoforming for manufacturing, and in combination with hybrid composites for engineering resins. Some industrial uses for this product include fabrics, rigid and flexible packaging, photoelectric modules, thermoset resins, and watertight barriers. Geotechnical engineering uses fibers and/or crushed particles in various shapes and sizes to improve soil characteristics. Numerous academics have researched the use of PT components in improving soil. Sinha et al(2019) .'s study examines soil behavior in the presence of PT components during the CBR test. Maher and Ho (1994) performed a triaxial cycle test to ascertain how PT contents in cemented sand behaved. Uniaxial compression tests were performed on strengthened cohesive soil with PT trash by Li and Ding (2002) and Babu and Chouksey (2011) to examine tension responses. Therefore, 1% reinforced soil offered larger tension angles, higher uniaxial strengths, and 73.8% more strength than unreinforced soil. Consoli et al. (2018) employed PTs that contained 0.9 percent of the weight of the soil. The size of the PT pieces in their investigation was around 36. (mm). The outcomes demonstrate that PT improves mechanical properties such as soil strength.

Acharyya and Raghu (2013) looked at how PT enhancements affected the performance of sandy and clayey soils. Their research indicates that sandstone soils are superior to clayey soils for PT reinforcement. The study discovered that sandstone soils are more likely than clayey soils to gain from PT reinforcement. Soft clay soil has a lower optimal wet percentage than sand, whereas sand has a larger optimum reinforcement content. Clayey soils were also the subject of investigation by several scientists (Alvarez et al. (2020) and Louzada et al. (2019)). Botero et al. (2015) performed a cohesionless poorly consolidated triaxial test with various equivalent pressures (2.5, 5, 7, and 7.5 m) and PT contents (0, 0.3, 0.6, and 1%). PT reinforcements are responsible for a decrease in the friction angle and an increase in cohesiveness. A number of tests on PT reinforcements were reportedly carried out by Peddaiah et al. (2018) as well as Necmi and Ekrem (2020). By using cement, plastic bags, PT components, and PT fiber as reinforcement, the resistivity rate of sandy soil at Babol port, Iran, was examined. It was discovered that among fiber reinforcing techniques, 1% of fiber reinforcement enhanced shear strength the most (Ranjbar Malidarreh et al., 2018). The performance of composite material under direct shear and triaxial test was also studied by Patil et al. (2016). When PT content was added to the soil, a sizable improvement in soil cohesiveness and strength was seen.

Moghaddas Tafreshi et al. (2021) investigated the cyclic response of reinforced soil during cyclic testing. All four groups of researchers—Shariatmadari et al. (2010), Fathi et al. (2010), Hafez et al. (2019), and Carvalho et al. (2019)—have shown how PT affects the pore water pressure, seismic behavior, and preservation of pedestrian soil in reinforced soil as well as the drainage conditions and conditions. Mishra and Kumar Gupta (2018) also investigated the effects of PT and Fly ash combinations in clayey soil .The literature study shows that PT can greatly boost both soil parameters and those of other conventional soil enhancement products. However, a more thorough investigation is required to ascertain the scope and impact of the upgrade. Numerous research have successfully shown how to represent geotechnical problems and thoroughly investigate them in various domains using artificial intelligence algorithms (Naghadehi et al., 2019; Samaei et al., 2020; Sammie et al., 2018). As a result, in this work, reinforced sandy soil containing PT components is anticipated using novel models and computer algorithms.

2. Dataset

2.1. Soil

Sand from Anzali Harbour in Iran was employed in the current study as reinforcement together with waste polyethylene terephthalate (PT) plastic material. The soil underwent testing to determine its mechanical characteristics first. Sieving, specific gravity (Gs), and a number of tests to establish the specific weight of soil in order to apply the preferred relative density (Dr) to the soil as well as tests to establish the characteristics of PT, such as specific gravity, modulus of elasticity, and tensile strength, were all included in the tests. The reinforced samples underwent the direct shear test after being reinforced with dump.

According to the Unified Soil Classification System, the sandy soil employed in this study was carbonated sand with coarse grains, rounded corners, and uniformity, which belonged to the poorly graded sand (SP) class. Additionally, all of the studies were conducted in a dry environment on this soil. Table (1) shows the additional mechanical characteristics of the soil that were determined by testing.

Table 1 Mechanical properties of sample soil

properties	Gs	e_{min}	e_{max}	γ(d)min gr/cm3	γ(d)max gr/cm3	D50 mm	Cu	Cc
	2.65	0.65	1.12	1.6	1.25	0.17	1.25	1.07

The distribution of particles larger than 0.075 mm (soil remaining on the 200 sieves) was determined by conducting a granulation test by sieve. Since the percentage passing through the 200 sieve was very low (less than 1% by weight of the soil), the soil was considered coarse grain material, and there was no need to conduct a hydrometric test.

Table 3 Statistically description of parameters used in this study

Category	Symbol	Unit	Min	Max	Avg	St deviation
Input	PT type	-	1	3	1/846	0/772
	Dr	%	0/55	0/95	0/75	0/164
	Sn	kPa	50	150	100	41
	PT percentage	%	0	2	0/6	0/68795
Output	Shear Strength	kPa	36/31	144/63	84/88	31/903

As shown in the size distribution curve, the diameter range of grains is very narrow, and most of the grains are in the same dimension range. In other words, this is poorly-graded sand or the SP soil in the USCS.

In order to investigate the effect of relative density on soil shear strength parameters, reinforced soil samples were made with three relative densities of 55%, 75%, and 95%.

2.2. PET

The pieces of PET used in the experiments of this research were obtained by cutting plastic bottles in the form of chips 1×1, 1×5 cm and with a thickness of 0.5 mm or in the form of fiber. PETs are obtained by thoroughly washing, drying, and then crushing waste plastic bottles. The PETs used in this study are shown in Fig (3). The measured characteristics of the PET used in the research are written in Table (2).

Table 2 Properties of PET elements

length(mm) and width(mm)	Thickness (mm)	Gs	Chemical formula
10 × 10 10 × 50 Fiber	0.5	1.38	$(C_{10}H_8O_4)_n$

To compare the shear strength of the soil with and without PT reinforcement, direct shear tests were performed. According to the ASTM D 3080-90 standard, tests were conducted on materials with relative densities of 55%, 75%, and 95% in the dry condition, up to a strain of 10%, at a constant speed of 2.067 mm/min, and under three different normal stresses (Sn) of 50, 100, and 150 kPa. 118 sample test data were utilized as a dataset to create tree-based models. All the parameters, including PT type, PT %, Dr, Sn, and shear strength, were assessed in this context. Basic descriptive statistics for all parameters are shown in Table (3) (input and output). The statistical indicators revealed a reasonable range.

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3. Model's Background

3.1. Decision trees

As an important part of machine learning and data mining, the supervised-learning decision tree (DT) has been introduced to perform both classification and prediction modeling. Several subsets are available for DT, e.g., chi-squared automatic interaction detection (CHAID), quick, unbiased, efficient, statistical tree (QUEST), C5, and classification and regression trees (CART). Out of these methods, only CART and CHID predict and model continuous variables. Furthermore, due to the white-boxed nature and simple interpretability of CART algorithms, understanding the relationship between input and output parameters and outstanding become easy. CART results are not affected by large-scale datasets, and this algorithm shows its superiority when dealing with complex samples and a high number of variables.

According to Samaie et al. (2018), the CART method to identify the most influential input parameters employs a principal component analysis (PCA) and eliminates non-significant ones. CART DT can be developed as a classification tree (CT) or regression tree (RT). main indices influence the performance of a CART for a given dataset to select the best partition. There are three main indices for a CT: Gini criterion, Entropy, and Twoing criterion. Also, due to the non-parametric temperament of CART, the assumption of the distribution of variables is not mandatory. Generally, root, branch, node, and leaf are the four parts of the CART method. Each tree starts from the root node (the first node), located at the upper level of each tree, and divides into sub-branches at the left and right sides (see Fig. (1)).

Three prevention criteria, (1) minimum number of observations, (2) maximum tree depth, and (3) reaching least error value for estimation of a dependent parameter, are available for a CART model development. Using these criteria, a CART training algorithm can be restricted from developing a complicated tree or overtraining. The verification dataset will simplify the developed tree and attain the optimum subtree. The simplification procedure also reduces the occurrence of overtraining. A decision tree consists of a root node, decision nodes (interior nodes), and terminal nodes (leaf nodes). Each dataset sample is classified from the root node until it is impossible to divide into decision nodes and attains a terminal node (Fig. (1)).

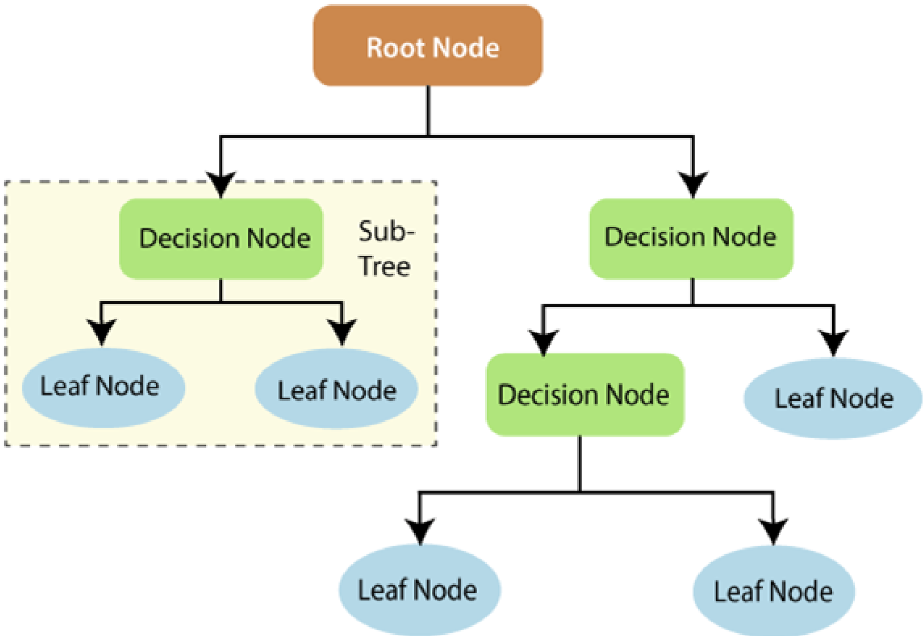


Fig.1.A Decision Tree consisting of the root nodes, decision nodes, and terminal nodes

3.2. Random forest

The random forest (RF) algorithm was developed based on the CART decision tree algorithm by Breiman (2001) and can combine a large number of DTs to develop a single model. Zhou et al. (2020) showed that it could be used as a classification or regression method without making any prior assumption on their association with the response variable. At the first step of the RF algorithm, samples are created according to the bootstrap sample selection of the dataset, and each of bootstrap-created sample makes an RF tree. As well as the out-of-bag (OOB) samples, unused samples during the bootstrap selection process, are used in the validation step. The RF algorithm is schematically shown in Fig. (2).

Probst et al. 2019 showed that The structure of each tree in RF can be controlled by (i) minimum node size, (ii) number of trees, and (iii) level of randomness. Some advantages of the RF algorithm are: (a) developed trees can be saved and used for future references, (b) is not susceptible to overfitting problems, (c) lower training time and faster prediction, and (d) embedded feature selection makes it easy for RF to rank parameters by importance, which makes RF algorithm unique in comparison with other machine learning techniques (Witten et al., 2005).

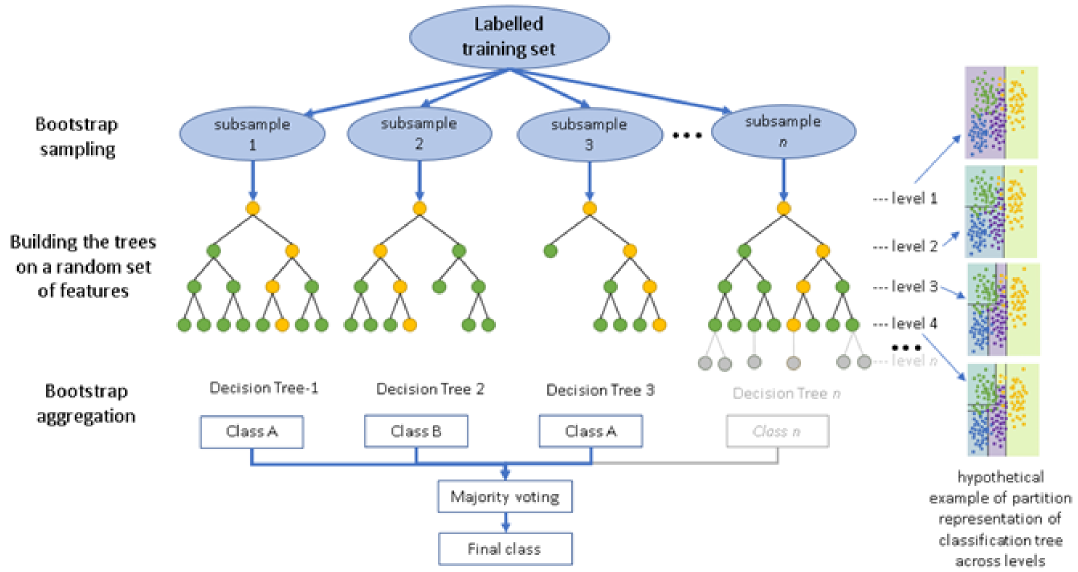


Fig.2.the process of random forest trees' growth

It is also important to note that the splitting feature of the RF algorithm is one that provides efficiency. Gini-index splitting criterion is commonly used in previous studies (Resende and Drummond 2018). In this study, due to the use of the Scikit-Learn Python library (Pedregosa et al., 2011), two splitting (Gini-index and Entropy) were available. Hence, both of those methods are examined. Gini index uses the impurity of nodes to measure the minimum error rate for the set. And also, the Entropy method measures the information in a data group and splits the tree to give more information. If the Entropy is extended, the subsets homogeneity gets better (Kuhn and Johnson 2013).

4. Performance Indices

In this study, four AI models were developed to predict soil's strength improvement by PET elements, including a Decision Tree, Random Forest, Extreme Gradient Boosting, and Adaptive Boosting algorithms. The datasets were randomly divided into training (75%) and testing (25%) subsets. The performance of each model is evaluated with popular indices, including Determination Coefficient (DC, R^2), Root Mean Square Error (RMSE), Variance Account For (VAF), and A-10 index (Naghadehi et al. 2018; Samaie et al. 2018). Respectively, these indices are as follows (equations (to)):

$$\mathbf{R^2 = 1 - \frac{\sum(y_{act} - y_{pre})^2}{\sum(y_{act} - \bar{y}_{act})^2}} \quad (1)$$

$$\mathbf{RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_{pre} - y_{act})^2}{n}}} \quad (2)$$

$$\mathbf{VAF} = [1 - \frac{var(\mathbf{y_{act} - y_{pre}})}{var(\mathbf{y_{act}})}] \quad (3)$$

$$\boldsymbol{a10 - index} = \frac{m10}{N} \quad (4)$$

where, $\mathbf{y_{act}}$ and $\mathbf{y_{pre}}$ are measured and predicted values, respectively. N is the total number of datasets, and $m10$ is the number of samples with values of rate measured/predicted value (range between 0.9-1.1).

5. Modeling Procedure

An explanation of how each method was developed will be presented in this section. Detailed descriptions will be given of each sub-relative section's parameters, ideal parameters, and significance in optimizing algorithm performance.

5.1. Decision Tree

Optimizing the learning process affects the decisions made by the decision tree. A Python library called SciKit Learn was used to create DT, and the Graphviz library was used to visualize the data. When used as a feature selection criterion, mean square error (MSE) is similar to variance minimization (Friedman, 2001, 2002). As a method of locating splits, Friedman-MSE uses mean square error along with Friedman's improvement score (Hastie et al., 2009).

To divide an internal node, the minimal samples' split is used. Due to its significance, this parameter is set to two, which increases the likelihood of the tree making accurate predictions. Leaf samples are specified by the terminal node. In order to continue optimizing accurately to the highest level, it was selected as one. Through tree depth control (TD), a tree can avoid overgrowth and overtrain. Out of a group of created trees, this variable is one of the primary factors that determine the best tree (Samaei et al., 2020). Lower depths are better than higher depths because TD is more likely to memorize data. The parameters mentioned above were used to develop DTs to predict reinforced soil behavior. DT parameters can be optimized for the best model to predict reinforced soil strength as shown in Table 4. A trained DT is also shown in Fig. (3) with regard to reinforced soil predictions.

DT enables infomercial ranking of the input variables in accordance with their relative relevance. According to this ranking system, the input variables that are most likely to be crucial to tree division and accurately forecasting target values are those that are located nearest to the root.

Table 4. The optimal values of DT parameters for generation flyrock

Parameter	Range	Optimum value
Pet elements value (%)	[0.1, 0.5, 1 and 2]	1%
Soil density (%)	[55, 75, and 95]	95
Pet type	[(1*1), (1*5) and fiber]	1*1
Normal stress (Sn)	[50, 100, and 150 KPa]	150

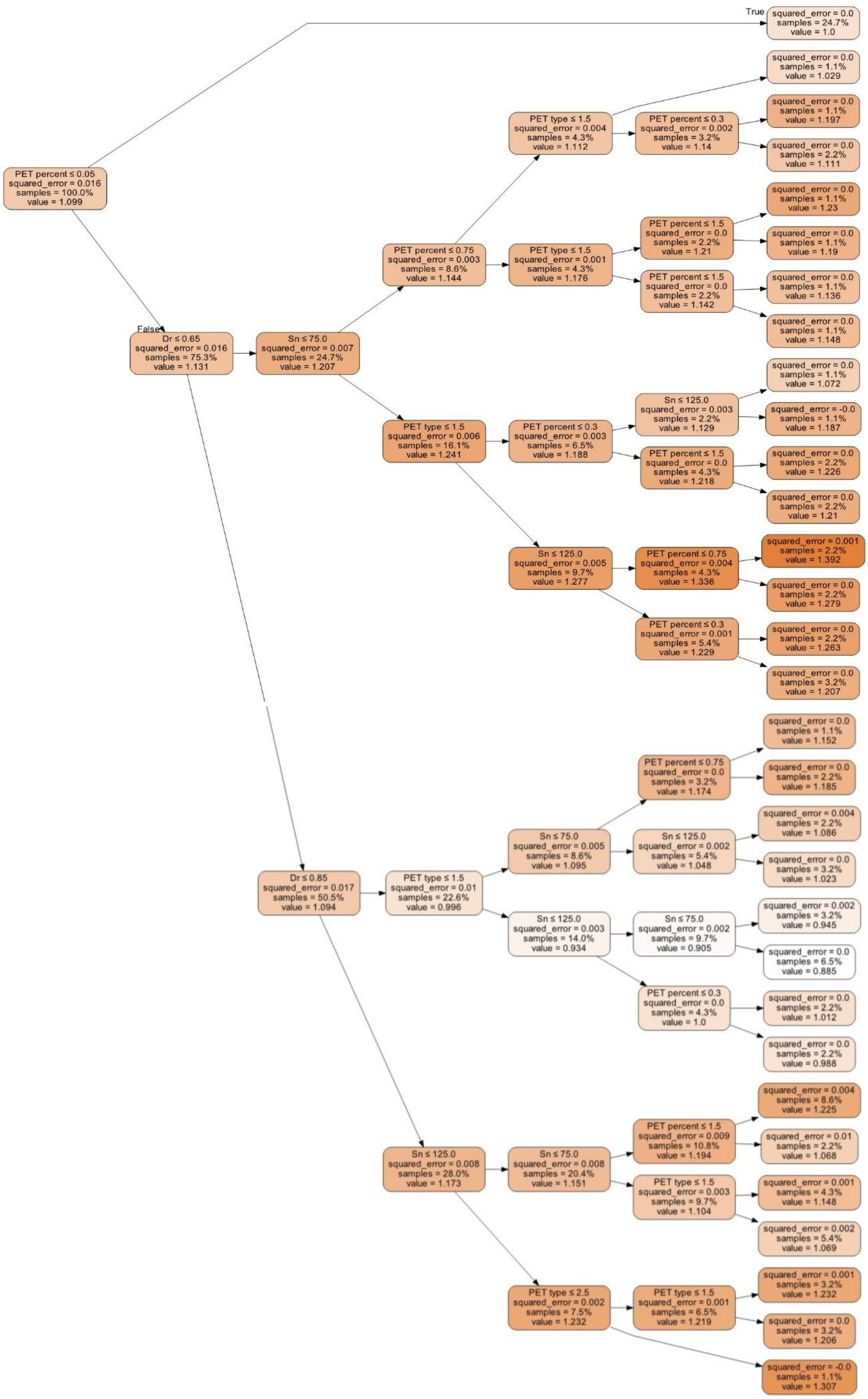


Fig.3.DT model for PT prediction

There are no PT components or additions present in the first arm of the DT. A value of one was assigned to this sample by the DT algorithm, and its strength was compared to that of other reinforced samples. Values rise as sample strength increases, and this specimen's allotted box becomes darker. According to the algorithm, PT made the three samples looser, but also decreased their shear strength, resulting in brighter colors or sheer white colors. According to the tree's results, PT components had a very substantial impact on soil strength, with a 1.4-fold increase and higher value than previously suggested methods or materials.

5.2. Random forest

RF models of reinforced soil prediction were derived from the development data samples using the Bootstrapping sampling method. Based on the RF algorithm, DT samples are generated in a wide range to produce the most precise prediction. With the help of the RF algorithm, DT samples of varying sizes are created for accurate predictions. When the observations are calculated, an averaging system is applied to provide an accurate prediction. OOB assessment of training sets is set to True in the Python SciKit package code to evaluate the model's performance. In the bootstrapping process, the verification samples were excluded.

An estimate of the number of DTs produced from the RF run is revealed by the number of estimators in the RF run. As the number of classifiers increases, the significance of the variables increases as well. It has been found that adding more estimators to the method lengthens its execution time according to Lunetta et al. (2004). The results produced by this approach, however, are more reliable. To calculate TD, 200 estimators were selected after a lot of trial and error. In order to maximize performance, this strategy could cause the model to become overfitted. A trained DT is also shown in Fig. (4) To gather information, the Entropy criterion performed better than the Gini criterion. Table 5 provides a summary of additional crucial elements, along with their ideal values

Table 5. RF Hyperparameters for estimating flyrock

Parameter	**Range**	**Optimum value**
Criterion	[Entropy, Gini]	Entropy
Estimators number	[50, 100, 200, 300]	200
Bootstrap	[True, False]	True
Max depth	[3, 4, 5, 6, 7]	4
Max features	[sqrt, log2]	Sqrt
OOB score	[True, False]	True

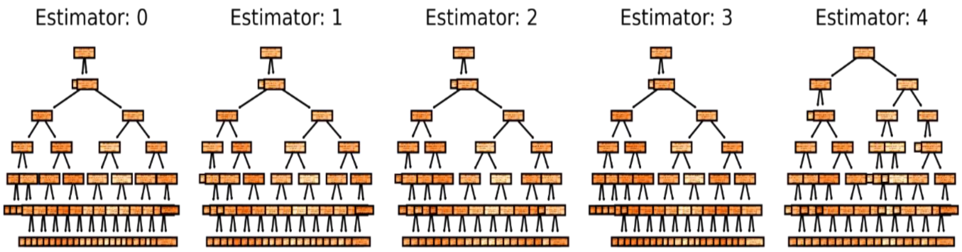


Fig.4.RF model for PT prediction

6. Results and Discussion

The purpose of this study was to predict the increase in shear strength of sandy soils due to the use of PT elements by using two tree-based techniques, i.e., DT, and RF. We evaluated each model's performance using four popular performance indices (R2, RMSE, VAF, and A-10).

The results of the training and testing phases for these tree-based models are shown in Table 6. Zorlu et al. (2008) introduced a ranking system to compare the accuracy of the developed models. As shown in Table 6, RF, which uses the DT classifier in its core algorithm, achieved the highest prediction accuracy, with a final ranking of 15. RF also been found to perform better in prediction than DT. The datasets used in the current study have not been used in any other studies. Meanwhile, the authors tried to compare the results with similar studies in the literature; however, a similar study could not be found.

Table 6 Ranking of developed models based on performance indicators

		R^2		RMSE		VAF		A10		Final rank
Model name		train	test	train	test	train	test	train	test	
Random Forest		0.95	0.87	0.03	0.05	94.32	87.14	1	1	
	Rank score	2	2	1	1	2	3	1	3	15
Decision Tree		0.94	0.83	0.03	0.05	93.71	82.77	1	0.92	
	Rank score	1	1	1	1	1	1	1	1	8

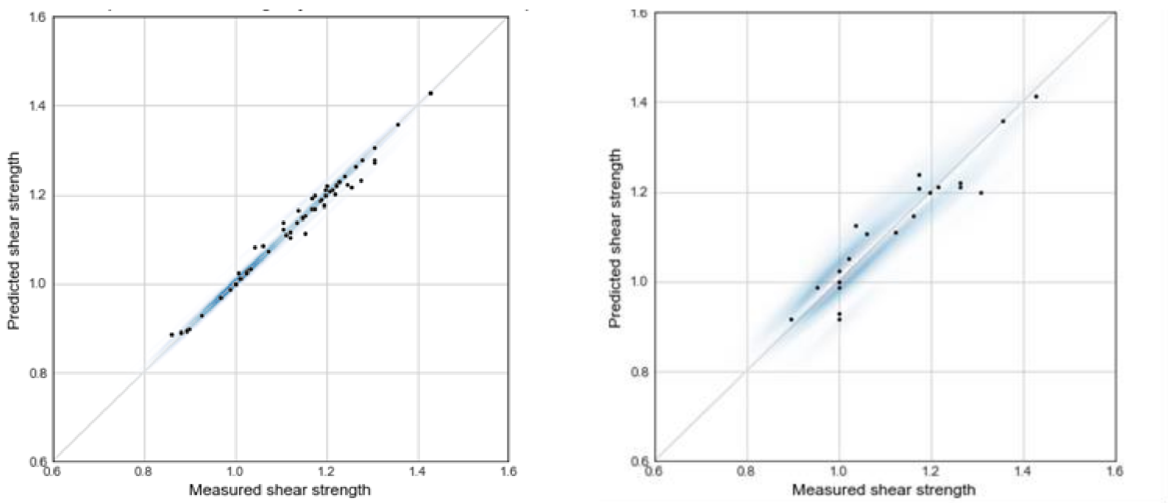
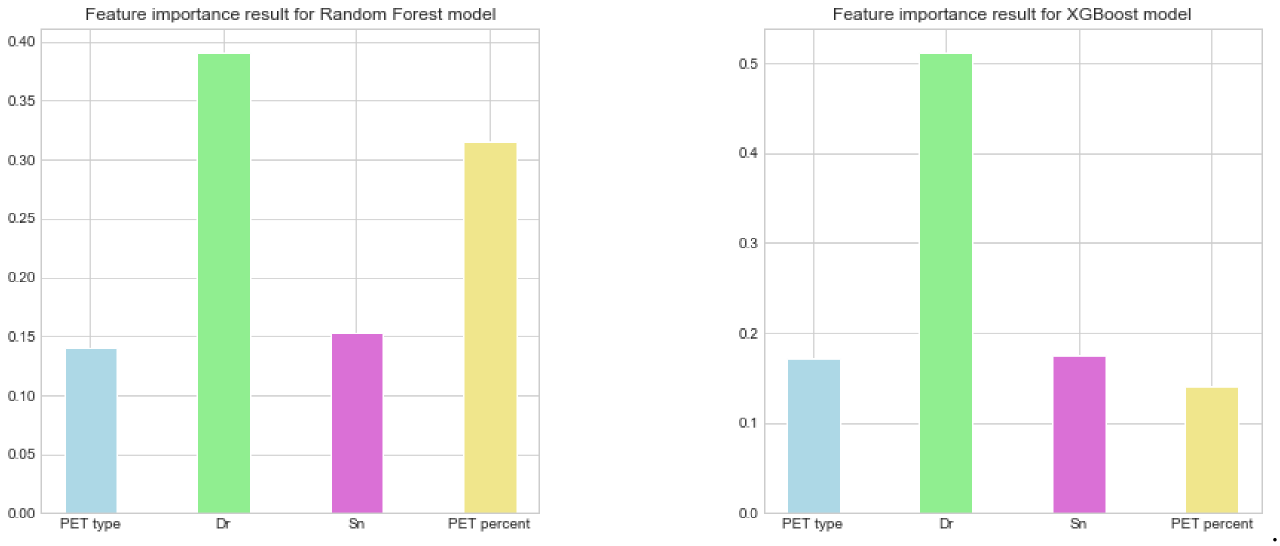


Fig.5. The graphs of measured and predicted shear strengths for the training (R^2=0.95) and testing (R^2=0.87) datasets for RF mod**el**

As shown in Fig. (5), the predicted and measured shear strengths of the RF model correlate. In order to help understand how the data were distributed and concentrated, plots were tinted in different hues. There is no doubt that RF makes highly accurate forecasts of shear strength improvements, which match those typically observed.



(a) (b)

Fig. 6. Feature importance analysis (a) RF, (b) DT

While creating the model, the settings for the RF and DT algorithms are shown in Fig. (6). The relative density parameter plays an important role in all algorithms. PT percent is then discovered to be the second most critical parameter for the algorithms. There is also a greater significance to normal stress in all the approaches than to PT type.

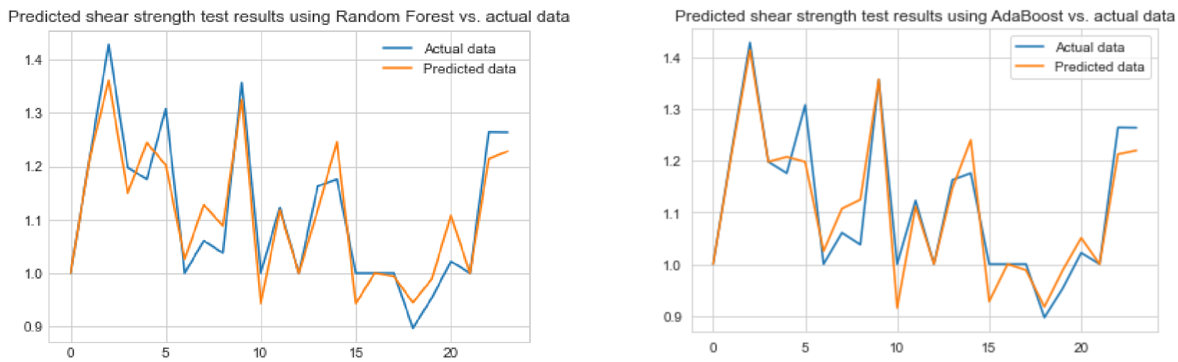


Fig.7 Correlation between the measured and predicted data for the developed models

The observed and algorithm-predicted numbers for several samples are displayed in Fig. (7). The least difference between measured and anticipated values may be seen in the RF model.

Conclusion

This work led to the creation of a tree-based predictive model for the forecasting of PT component increases in the shear strength of the ground. Based on empirical investigations, the DT and RF models were created to forecast shear strength. These numerical simulations specifically looked for the best model parameters for tree-based models. When comparing the performance of the DT and RF models, the RF model performed better with R2train=0.95 and R2test=0.87. Further indices were utilized to assess each model's performance, including RMSE, VAF, and A10-index. As a result, upon the other indices, the RF model appears to be the most reliable in terms of prediction. RF used a learning algorithm in the sequential learning process as a component of the consecutive learning process. These trees are similar to DT in many ways, but RF merged and learned from them to try to minimize mistakes. RF grows the tree without raising error rates by learning from earlier rounds. Based on earlier RF model findings, a low-noise dataset improved performance. As long as you have skilled users and enough time to fine-tune the input parameters, you may utilize this approach if computing expense, complication, or speed of findings are unimportant.

Saturation circumstances, parameter limits, and other significant parameters must be identical to or extremely close to those in this research in order for the estimate to be true. Additionally, findings will have larger failure rates if inputs are submitted beyond the range stated in this study. Through the application of empirical equations and concepts during data preparation, theory-guided machine learning can enhance performance prediction. These methods could eventually allow us to comprehend geotechnical engineering better. These models are helpful for making assumptions models, which is one of the drawbacks of AI models, at least in engineering.

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