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Data-Driven Modeling of Ultimate Load Capacity of Closed- and Open-Ended Piles using Machine Learning

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Abstract

Field pile load tests are fairly expensive experiments that can be applied to certain pile types required to be installed in full scale. Hence, it is neither practical nor efficient to perform a load test for every installed pile. While there exist many empirical relations for predicting pile capacities, such methods typically suffer from accuracy and generality. Therefore, current geotechnical practice still looks for methods to accommodate full-scale pile load testing to serve as both accurate and practical tools. In this study, load bearing capacities of closed and open-ended piles in cohesive and cohesionless soils are predicted using machine learning. Nine such methods are utilized in the analyses where CPT and pile data are considered as the learning features necessary to teach those methods the database gathered via a comprehensive search. Then, machine learning models are developed, and the databases are separated into five-folds according to the cross-validation-principle, which are used for both training and testing of the machine learning methods. Model predictions are validated with classical empirical equations. Results indicate that the Relevance Vector Regression and the Random Forest methods typically generate considerably better predictions than the other methods and empirical equations. Hence, machine learning methods are found as reliable tools to predict the pile load capacities of both open-ended and closed-ended piles provided that there is a large enough database and an appropriate method to use.

Keywords: Cone penetration test, machine learning methods, pile load capacity, Random Forest, Relevance Vector Machines, static load test

1. Introduction

With the extent of advanced computer technology, machine learning has become one of the hottest topics in computer science that are increasingly being applied to solving civil engineering problems in the last few decades (Reich 1997). From the statistical distributions of relevant parameters associated with the design and analysis of engineering systems to the prediction of material behavior utilized in developing theoretical procedures in estimating load bearing capacities, one takes advantage of advanced technology such as machine learning methods (MLM). For that matter, many MLM have been developed over the years that constantly improve in accuracy and efficiency. Lately, those methods are found useful in geotechnical engineering essentially to predict bearing capacities of foundation soils from laboratory and/or field experiments (Shahin 2016).

Predicting bearing capacity of piles from Cone Penetration Test (CPT) results is a compelling task that is investigated by many researchers over many years. Abu-Farsakh and Titi (2004) evaluate the reliability of traditional CPT based pile capacity design methods on driven piles. Laboratoire Central des Ponts et Chaussées (LCPC) methods introduced by Bustamante and Gianselli (1982) and De Ruiter and Beringen (1979) show better predictive performance than other methods used by (Abu-Farsakh and Titi 2004). Also, Schmertmann-Nottingham method (Schmertmann 1978) provides reliable results on the load capacity of piles. Another study on the subject is Eslami and Fellenius (1997) which proposes a direct method named UniCone to estimate pile bearing capacity from CPT with pore pressure measurements (CPTU). Thereafter, an enhanced procedure is proposed to improve this method (Niazi and Mayne 2016). Clausen et al. (2005) propose the NGI approach of bearing capacity of driven piles in sand, while Jardine et al. (2005) present comprehensive design methods for driven piles in both sand and clay. Then Lehane et al. (2007) develop the UWA-05 method for the bearing capacity of open and closed driven piles in siliceous sand from cone tip resistance.

In the last three decades, artificial intelligence (AI) techniques are increasingly applied to civil and geotechnical engineering problems (Zhu et al. 1998; Banimahd et al. 2005; Johari et al. 2006; Lamorski et al. 2008; Yurtcu and Özocak 2016; Dağdeviren and Kaymak 2018; Mohanty and Das 2018; Alzo'ubi and Ibrahim 2019; Kumar and Samui 2019). Predicting the load capacity and settlement response of

shallow and deep foundations by MLM needs more comprehensive studies due to irregularity among the results and requirement of large datasets. Artificial Neural Networks (ANN) is perhaps the earliest of such methods applied to studies related to capacity predictions (Lee and Lee 1996; Teh et al. 1997). Shahin et al. (2002) use a conceptual algorithm to estimate the settlement rate of shallow foundations. Samui (2008) applies the Support Vector Machine (SVM) algorithm for prediction of shaft capacity of piles from pile geometry and effective overburden pressure. Ardalan et al. (2009) estimate pile shaft capacity from CPT results utilizing the Polynomial Neural Networks (PNN) and Genetic Algorithms (GA). Pal and Deswal (2010) predict axial bearing capacity of piles including tip and shaft resistances using the Gaussian Process Regression (GPR). The results show that the methods of SVM, PNN, GA, and GPR demonstrate better predictive performances than the traditional methods given above (Schmertmann 1978; De Ruiter and Beringen 1979; Bustamante and Gianselli 1982). More recent studies are conducted on predicting the load-settlement behavior of piles by applying optimized neural network algorithms (Ismail and Jeng 2011; Ismail et al. 2013). Besides, Debnath and Dey (2018) and Moayedi and Hayati (2018) contribute to predicting load bearing capacity and settlement of piles through AI techniques. Shahin (2016) summarizes the recent ML techniques used for solving geotechnical engineering problems.

Estimating axial pile capacity from CPT results through ML regression algorithms has been increasingly used. Shahin (2010) examines the performance of an ANN algorithm for 80 driven piles and 94 drilled shafts using full-scale static load tests and CPT results. The performance of their ANN model is analyzed in terms of two statistical metrics namely R-square (R^2) and Root Mean Squared Error (RMSE). According to their study, the ANN method shows a better performance in predicting the drilled shaft capacity than the driven piles. The reason for this may be related to the characteristics of the collected database or using more data for training the model. Gene Expression Programming (GEP) is used to build a new correlation between pile capacity and CPT data in cohesive soils by Alkroosh and Nikraz (2011, 2012). Although the model is based on analyzing a relatively less number of data, satisfying results are achieved. The SVM algorithm is implemented by Kordjazi et al. (2014) for the first time, then the predictive performances of three types of kernel functions are evaluated. Their study shows that SVM is a withstanding method for predicting the bearing capacity of piles using a multi-national

database containing 108 case histories. Shortly after, Alkroosh et al. (2015) develop a new model for bored piles with the Least Square Support Vector Machines (LSSVM) method. Ebrahimian and Mohaved (2017) propose two formulations for predicting the axial capacity of piles in cohesive and cohesionless soils applying the evolutionary based approaches. These models are verified in the field with two full-scale pile load tests which are not used for training or testing. Adaptive Neuro Fuzzy Inference Systems (ANFIS) is another MLM for predicting the bearing capacity of piles from CPT results (Ghorbani et al. 2018; Harandizadeh et al. 2019). Kardani et al. (2020) apply six different MLM to a relatively small number of data for predicting axial capacity of piles. However, outdated pile load tests with a most recent one from 1984 and insufficient number of data for generalizing the whole population can be counted as the drawbacks of this study. While there has been considerable research on using MLM that estimate the pile load capacity, most of these studies focus solely on the predictive abilities of a single or a small group of methods. As computer technology advances and mathematical applications are more and more used on enhancing the capabilities of such methods, new MLM are developed leading to better approximations being expected in the analysis of piles. Thus, in this study, nine of those most common MLM namely the Ridge Linear Regression (RLR), Multivariate Adaptive Regression Splines (MARS), k-Nearest Neighbors Regression (kNNR), Decision Trees (TREE), Random Forests (RF), Extreme Learning Machines (ELM), Relevance Vector Regression (RVR), Gaussian Process Regression (GPR), and Variational Heteroscedastic Gaussian Process Regression (VHGPR) are used to predict the axial load bearing capacities of closed-ended and open-ended piles. Static pile load tests as well as CPT data are used in gathering the training and the test datasets.

2. Machine Learning Methods

Machine learning (ML) is an efficient data-driven approach used to model the relationship between input and output of a system. In order to develop such a representative model, a bulk of data obtained from experiments or observations is represented with a high dimensional feature vector, which is then mapped onto an output-space via a regression function. The weights of the parameters in the regression function are estimated by minimizing a loss function defined by the corresponding MLM. Linear regression methods provide an explicit predictive model, making them more interpretable than the nonlinear methods and allowing for analysis of parameters' effects on the model output. On the other hand,

nonlinear methods provide an implicit function such as a black-box model achieving higher performance than linear methods, but with less interpretability. This is especially the case when a nonlinear behavior exists in the input-output variables.

In this study both linear and nonlinear regression methods are used, which are summarized in the following subsections. We focus more on providing a general understanding of the regression methods rather than a rigorous theory and technical details. Interested readers are referred to related references

2.1 Linear Methods

Ridge Linear Regression (RLR):

RLR is a variant of linear regression, which shrinks regression weights by imposing a penalty parameter to an optimization problem, to overcome overfitting which may result in a simple linear regression. In linear regression, we have the following model,

$$f(x_1, \dots, x_n | w_1, \dots, w_n) = w_0 + w_1 x_1 + \dots + w_n x_n \quad (1)$$

where w_i refers to the weight associated with the parameter, x_i . The loss function of the ridge regression is defined by penalizing residual sum of squares as follows:

$$\min_{w_1, \dots, w_n} \sum_{j=1}^m ||f(x_1^j, \dots, x_n^j | w_1, \dots, w_n) - y^j||^2 + \lambda \sum_{i=1}^n w_i^2 \quad (2)$$

where λ is the regularization parameter, controlling the smoothness of the linear model, while the last term in Eq. 2 is called l_2 norm regularizer. The loss function is minimized by taking the partial derivatives with respect to each parameter of the linear model and setting them to zero, yielding the following system of linear equations:

$$w = (X^T X + \lambda I)^{-1} A^T y \quad (3)$$

where I refers to an $n \times n$ identity matrix, and y is a vector that holds all the outputs associated with given observations. The linear model can be obtained as in Eq. (1) once the weights are calculated.

Multivariate Adaptive Regression Splines (MARS):

MARS is a multivariate nonparametric regression method which can be viewed as a generalization of stepwise linear regression (Friedman 1991). MARS is capable of modeling nonlinearities and interaction between the variables, which is ensured by fitting piecewise q -th order polynomials, also called basis functions. The learning model provided by MARS is expressed as follows:

$$f(x) = w_0 + \sum_{j=1}^q w_j P_j(x) \quad (4)$$

where q is the number of basis functions included in the MARS regression, and w_j is the coefficient of the j^{th} basis function P_j , which might be either a single spline function or which may define the interaction between two or more spline functions. The method has two steps: i) Creating a collection of basis functions based on a given dataset, ii) Conducting a least square regression to find the weights of those basis functions.

2.2 Nonlinear Methods

k-Nearest Neighbors Regression (kNNR):

kNNR is a non-parametric regression method using a strategy based on the similarity between the samples in the input space. To predict the output value (y_i) for a given sample (x_i), a neighborhood set is first determined using the k -nearest neighbors of the corresponding sample according to Euclidean distance. The output value is then calculated as the average value of the outputs, those with k -nearest neighbors of the corresponding sample. Therefore, the *kNNR* does not provide an explicit learning model for output prediction since it directly requires training samples at each stage of the prediction.

Decision Trees (TREE):

TREE is a nonparametric learning method based on a set of hierarchical nodes each of which performs a decision tree algorithm with a testing function, $f_m(.)$ using individual input features. Here, m refers to the number of nodes. Given an input, each $f_m(.)$ divides the n -dimensional feature space into smaller regions where subdividing operations are consecutively performed until reaching the end of any leaf of the decision root. Each node has an output label, which is a numerical value in the case of regression. Different decision models can be generated depending on the type of the $f_m(.)$ function. The main advantage of the decision tree model is its interpretability because each path from the root to the leaf can easily be converted into a set of “if/else” structures that are quite understandable. In terms of providing an explicit learning model, a decision tree consists of a set of rules to be performed for predicting the output value.

Random Forests (RF):

The classical decision tree algorithm cannot cope with strong nonlinear relations between input and output; hence, a combination of decision trees can improve the performance further. RF consists of a collection of randomized base tree classifiers, each of which is constructed by some partitioning rule such as the random split selection or the random input selection (Breiman 2001). RF is an ensemble-based highly robust method used for classification and regression. Prediction of the output for a given sample is simply determined by averaging the predictions estimated from each tree when used for regression.

Extreme Learning Machines (ELM):

ELM is a learning algorithm that allows performing nonlinear, multivariate regression for generalized single-hidden-layer feedforward neural networks, which has one hidden layer and one linear output layer (Huang et al. 2006). ELM is much faster than traditional neural networks since hidden-layer node parameters are randomly selected and the output weights are analytically computed using the least squares solution. The learning model of ELM is defined for a given input, x , as follows:

$$f_L(x) = \sum_{i=1}^L w_i h_i(x) \quad (5)$$

where L is the number of nodes at the hidden layer, and w_i is the output weight connecting the i^{th} hidden node to the output nodes. h_i represents a nonlinear feature mapping so-called *activation function* at each node, which is generally selected as a sigmoid function. Equation (5) can be written in a more compact form as:

$$\mathbf{H}\mathbf{w} = \mathbf{Y} \quad (6)$$

where $\mathbf{Y}^T = [\mathbf{y}_1, \dots, \mathbf{y}_n]$ is the output vector of the training set, and $\mathbf{H}$ is the hidden layer output matrix of the neural network. The optimal output weight, $\mathbf{w}$, is calculated by minimizing $\|\mathbf{H}\mathbf{w} - \mathbf{Y}\|^2$ in the least squares sense, yielding

$$\mathbf{w}^* = (\mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T\mathbf{Y}. \quad (7)$$

Relevance Vector Regression (RVR):

RVR is a probabilistic sparse kernel model identical in functional form to the support vector machines (SVM) (Tipping 2000). The RVR method is used for both classification and regression problems

providing a probabilistic prediction by adopting a Bayesian approach to the learning process. Unlike SVM, kernel function does not need to satisfy Mercer conditions, and there is no need for hyper-parameter tuning. The method assumes that the samples in the training dataset are normally distributed with zero means. The probabilistic learning model of RVR is given as follows:

$$p(y|\alpha, \sigma^2) = (2\pi)^{-\frac{n+1}{2}} |\mathbf{B}^{-1} + \Phi \mathbf{A}^{-1} + \Phi^T|^{-\frac{1}{2}} \exp \left\{ \frac{-1}{2} \mathbf{y}^T (\mathbf{B}^{-1} + \Phi \mathbf{A}^{-1} + \Phi^T)^{-1} \mathbf{y} \right\} \quad (8)$$

where $\mathbf{A} = \text{diag}(\alpha_0, \dots, \alpha_n)$ and $\mathbf{B} = \sigma^{-2} \mathbf{I}_n$. The parameter, σ , is determined using the training set, and α is calculated based on solving an optimization problem. The matrix Φ is called kernel functions $\Phi = K(x, x_i)$.

Gaussian Process Regression (GPR):

GPR, also known as the Kriging method in statistics, is a non-parametric Bayesian multivariate regression method, defined as a collection of random variables with a joint Gaussian distribution. The Gaussian Process (GP) is defined as follows:

$$f(x) \sim GP(m(x_i), k(x_i, x_j)) \quad (9)$$

where $\mathbf{x}$ and $\mathbf{k}(\mathbf{x}_i, \mathbf{x}_j)$ correspond to mean and covariance function, respectively. The covariance matrix shows similarities between the pair of random variables, which can be built by means of squared exponential (SE) kernel function. Given a sample x_* , desired learning model, f_* , is obtained as follows:

$$p(f_* | x_*, x, f) = N(f_* | \mu_*, \sigma_*) \quad (10)$$

where

$$\mu_* = \underline{k}_*^T \cdot [K(x, x) + \sigma_n^2 I]^{-1} \underline{y} \quad (11)$$

$$\sigma_*^2 = k(x_*, x_*) - \underline{k}_*^T \cdot [K(x, x) + \sigma_n^2 I]^{-1} \underline{k}_* \quad (12)$$

Here, $\underline{k}_*$ is a vector of covariance values of training samples (x) and test sample (x_*), and σ_n^2 is the noise variance. The σ_x^2 expresses the confidence measure associated with the model output. It should be noted that the training data need to be attained in the analysis as GPR is a kernel-based regression method.

Variational Heteroscedastic Gaussian Process Regression (VHGPR):

In the standard Gaussian Process Regression, the variance for all observations is constant throughout the input space, which can be unrealistic in some problems. A model considering input-dependent

variance is known as *heteroscedastic* GPR (HGPR) (Lázaro-Gredilla and Titsias 2011), which is a variant and a special case of homoscedastic GPR. However, inference in HGPR is very challenging since the predictive density and marginal likelihood are no longer analytically tractable unlike in the homoscedastic case. To deal with this, a variational inference method is used for HGPR based on variational Bayes and the Gaussian approximation. The studies performed thus far show that variational methods are typically quite fast and accurate.

3. Database Details

3.1 Collection of the Database

In this paper, two different databases are gathered for closed-ended piles (CEP) and open-ended piles (OEP). Firstly, a wide database is gathered for CEP with 219 case history data collected from published studies, which include full scale static pile load tests, pile geometry, and CPT results. Various pile types such as driven piles, bored piles, and drilled shafts are considered in this database. In order to include the pile tip resistance as one of the features of the MLM predicting bearing capacity, pipe type OEP are excluded here. Piles made of concrete and steel with various cross section areas (i.e. square, round, and octagons) are all considered. Soil conditions are determined from the CPT data in terms of the cone resistance (q_c) and sleeve friction (f_s). Therefore, piles with available CPT data are used, and 145 of such pile data are taken from related sources (Alsamman 1995; Eslami 1996). The detailed database is given in the Appendix 1. Ultimate axial load bearing capacities of piles are determined by analyzing related load-displacement relationships of static pile load tests. Axial pile capacities are determined mostly as the failure loads except for the tests, where load-displacement relationships do not indicate clear failure loads for which the axial capacity is calculated as the average of the values obtained from the Chin–Kondner method, the Decourt method, and Brinch–Hansen 80% method (Fellenius 2001).

The second database constitutes 60 OEP load tests and CPT data with steel pipe piles embedded into non-cohesive soils. Also, the piles are subjected to static tensile loads. The ultimate bearing capacities are then determined based upon the friction capacities of the piles.

3.2 Model Input and Output

CEP Database:

The axial bearing capacity of piles is typically calculated as the sum of the tip resistance and the shaft resistance (Niazi and Mayne 2013). Therefore, the unit tip resistance around the pile tip and the unit shaft friction resistance over the embedded depth of pile as well as the pile geometries such as length and cross-sectional area are the main features necessary to calculate the pile capacity. Here five input features are selected: i) Embedded length of the pile, L ii) Cross-sectional area of the pile, A ; iii) Average of cone tip resistance around the pile tip, $(q_c)_{end}$; iv) Average sleeve friction along the embedded length of the pile, $(f_s)_{ave}$; v) Average cone tip resistance along the pile length, $(q_c)_{ave}$. The first two features are directly associated with pile geometry while the others are taken from the CPT results. Average cone tip resistance measured at the pile tip is taken as the geometric average of the cone resistance (q_c) along the influence zone defined by Eslami and Fellenius (1997). Geometric mean yields more accurate and repeatable values to analyze the CPT results as opposed to the arithmetic mean since it is less affected by the outliers. The influence zone is defined as the distance measured from $4D$ below the pile tip to $8D$ above it when the soils above the pile tip are weaker than they are below. Here D is the pile diameter. If the soil above the pile tip is dense, then the influence zone starts from $2D$ above the pile tip which decreases the effect of denser soils lying above. Figure 1a and 1b show the interpretation of the $(q_c)_{end}$ feature when the soil above the pile tip is weaker and denser, respectively. Other input features, $(q_c)_{ave}$ and $(f_s)_{ave}$, are determined by taking the geometric average of measured cone end resistance and sleeve friction resistance along the pile length. The first $2D$ distance is not considered due to soil disturbance. These processes are shown in Figure 1c and 1d. As for output, ultimate axial bearing capacity (Q_u) is the only variable, which is directly taken from the full-scale static pile load test results. The last feature is determined for only 120 data because of the missing sleeve friction values of the other 99 data. The description of the database for input features and the output are summarized in Table 1.

Figure 1. Interpretation of the input features from CPT results; a) $(q_c)_{end}$ for the soil above the pile tip is weaker, b) $(q_c)_{end}$ for the soil above the pile tip is stronger, c) $(q_c)_{ave}$, d) $(f_s)_{ave}$

Table 1. Statistical parameters of the input features and the output for CEP Database

<i>Input Features</i>						<i>Output</i>
	<i>Length (m)</i>	<i>Area (m²)</i>	<i>(q_c)_{end} (MPa)</i>	<i>(q_c)_{ave} (MPa)</i>	<i>(f_s)_{ave} (MPa)</i>	<i>Q_u (kN)</i>
Max	45	2.54	65.95	24.64	0.225	14590
Min	5.6	0.06	0.17	0.39	0.005	210
Range	39.4	2.48	65.79	24.26	0.221	14380
Std. Dev.	8.7	0.35	7.61	4.42	0.039	2224
Mean	14.6	0.25	9.42	5.64	0.059	2203
Number of data	219	219	219	219	120	219

Various CPT data used in this study include both mechanical and electrical data, making it necessary to convert mechanical CPT readings to equivalent electrical CPT values, the latter of which is the widely used CPT today. Kulhawy and Mayne (1990) compared the electrical and mechanical test results and proposed a correlation to convert the mechanical cone end resistance to related electrical values.

$$\left(\frac{q_c}{p_a}\right)_{electrical} = 0.47 \left(\frac{q_c}{p_a}\right)_{mechanical}^{1.19} \quad (13)$$

where p_a is the atmospheric pressure. It is also observed that the mechanical cones measure the sleeve friction resistance two or three times larger than electrical cones. Therefore, the sleeve friction readings taken from mechanical cones are converted down to electrical readings by a factor of two. Once all the input are prepared, feature scaling is applied to eliminate the dimensions. All the feature variables are reduced to suitable forms by applying a zero-mean standardization technique as follows:

$$x' = \frac{x - \bar{x}}{\sigma} \quad (14)$$

where x is the initial feature variable; $\bar{x}$ is the mean of the feature vector and σ is standard deviation.

OEP Database:

Similar to CEP, geometric measures and soil conditions are taken into consideration for determining the input features. In addition to L and A of the pile geometry, another geometrical feature, the *incremental filling ratio* (IFR), is also specified to mimic the pile-soil interaction better. IFR parameter that shows

the amount of soil plugged in is already used in the equations predicting the compression and tension capacities of OEP. According to Paik and Salgado (2003),

$$IFR (\%) = \frac{\Delta L}{\Delta D} \times 100(\%) \quad (15)$$

where ΔL is soil plug length in the small increment of pile diameter ΔD . It is necessary to measure the IFR at regular intervals during pile driving, however it is not applicable to practical works. Lehane et al. (2005) propose an equation to predict the average IFR along the pile length,

$$IFR \approx \min \left\{ 1, \left(\frac{D_i(m)}{1.5} \right)^{0.2} \right\} \quad (16)$$

where D_i is the inner diameter. Another novel feature used in the analyses is the number of *setup days* which represents how many days passed after the pile driving to the testing day. The reason for considering the time effect is a significant change in identifying the pile capacities among the piles with the same properties tested in different periods, which is discussed previously by (Chow et al. 1998; Schneider 2007). However, it is generally not considered in the design methods. Since the necessary information on days for setup has been available for every test, we have, therefore, decided to investigate the time effect in this study also. Lastly, the average cone tip resistance along the pile length similar to the CEP database, $(q_c)_{ave}$ is taken as the fifth feature. The description of the OEP database is given in Table 2.

Table 2. Statistical parameters of the input features and the output for OEP database

	<i>Input Features</i>					<i>Output</i>
	<i>Length</i>	<i>Diameter</i>	<i>IFR</i>	<i>Setup Days</i>	$(q_c)_{ave}$	Q_s
	(m)	(mm)	(%)	(Day)	(Mpa)	(kN)
Max	47.0	1220	95	1950	42.24	19482
Min	2.5	34	45	2	2.65	6
Range	44.5	1186	50	1948	39.59	19476
Std. Dev.	12.5	304	15	283	8.53	3875
Mean	15.4	432	72	163	11.12	2173
Number of Data	60	60	60	60	60	60

4. Training and Validation

Once the database is obtained and input-output variables are determined, the database need to be trained and validated. In this study, the k -fold cross validation technique is used to both train the database and validate its predictions. That is, five sets of data are gathered and four of them are randomly selected to be used to train the set with the MLM given in Section 2. Then a number of ML models are developed using internal mathematical functions generated as a result of the MLM. The predictions made using the test folds are then compared with the remaining single fold in terms of coefficient of determination (R^2) and relative error (RE). The flowchart developed in this study is shown in Figure 2.

4.1 k -Fold Cross-Validation

k -fold cross-validation is a methodology to evaluate the generalized performance of the learning method. The training dataset is randomly divided into ' k ' number of mutually exclusive subsets (folds) of approximately equal size. The MLM are trained on $k-1$ folds, and the remaining one is used for testing the performance of the learning model. This process is repeated k times in a way that each fold is used for testing only once. Expected performance is estimated by averaging the measure, which could be either in terms of the predictive error or predictive accuracy of the learning method over the k number of trials. The advantage of this method is that each sample is used only once in the test dataset and used $k-1$ times in the training dataset. When k is chosen as equal to the number of training samples, this refers to 'leave-one-out' cross validation, which is more computationally expensive than the k -fold cross validation due to the need to run the algorithm a total of k times. Note that a less amount of bias and high variance occur in the predicted results as the number of k increases. Therefore, an appropriate k value needs to be chosen depending on the size of the dataset to provide statistically significant results.

Figure 2. Flowchart of the proposed approach.

4.2 Performance Measurement

In this study, the statistical measures, R^2 and RE, are calculated to determine how close the predicted pile bearing capacities are to the actual values. R^2 is used to measure the goodness-of-fit indicating that if the fit is appropriate for a regression model. It is defined as:

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \quad (15)$$

where y_i and $\hat{y}_i$ correspond to the actual and the predicted value of the i^{th} sample, respectively, while $\bar{y}$ refers to the mean of the actual data. R^2 takes values between 0 and 1, where the closer it is to 1 the better the prediction (goodness of fit) gets. It is widely acceptable that there is a strong correlation if the correlation coefficient is greater than 0.8, which means R^2 gets larger than 0.64 (Sadrossadat et al. 2013). RE is the ratio of the difference between the predicted and actual value to the actual value as below:

$$RE = \frac{\|\hat{y}_i - y_i\|}{\|y_i\|}. \quad (16)$$

4.3 Classical Methods for Axial Pile Capacity

In this section, we revisit some of the classical empirical relationships to calculate the pile load capacity available in foundation engineering. Among the ones that exhibit sufficient accuracy for the piles considered in this study, three methods for each pile type, CEP and OEP, stand out. The results of these methods are then used in validation of ML predictions.

Schmertmann (1978) Method:

Schmertmann method (Schmertmann 1978) calculates the tip resistance of closed-ended piles in both sands and clays using the Begemann's procedure (Begemann 1965) of failure surface. Unit tip resistance of piles should be calculated as:

$$q_p = \frac{q_{c1} + q_{c2}}{2} \quad (17)$$

where q_{c1} is the minimum value of the mean cone tip resistance measured from pile tip to a distance from $0.7D$ to $4D$ below the pile tip with D being the pile diameter and q_{c2} is the average value of cone tip resistance measured from $8D$ above the pile tip to the tip itself. Unit tip resistance is limited to 15 MPa and the ultimate tip resistance can be calculated using the unit tip resistance and cross section area of the pile tip (A_{tip}). The shaft resistance is calculated separately for different types of soils in Schmertmann's method. Ultimate shaft resistance for clay is calculated as:

$$Q_s = \alpha' f_s A_s \quad (18)$$

and for sand as:

$$Q_s = K \left[\sum_0^{8D} \frac{1}{2} f_s A_s + \sum_{8D}^L f_s A_s \right] \quad (19)$$

where A_s is the pile surface area of the shaft interacting with the soil around; α' is the ratio of penetrometer friction to the pile friction in clay varying between 0.2-1.2; K is the ratio of pile friction to sleeve friction varying between 0.4-2.4, and f_s is the average sleeve friction at the corresponding depth. In clay soils, the unit skin friction is limited to a maximum of 120kPa.

de Ruiter and Beringen (1979) Method:

This method is developed by analyzing the load test results of offshore piles in the North Sea (de Ruiter and Beringen 1979). According to this method, unit pile tip resistance is calculated same as the Schmertmann's method for sands. In clay soils, unit pile resistance is obtained from the following equation:

$$q_p = N_c S_u \quad (20)$$

where N_c is the bearing capacity factor and equals 9 for internal friction of $\phi'=0$ condition. S_u is the undrained shear strength calculated as:

$$S_u = \frac{q_c}{N_k} \quad (21)$$

where N_k is the cone factor varying between 15-20, and q_c is measured at the corresponding depth. Unit shaft resistance varies also based on the undrained shear strength in clay and calculated as:

$$q_s = \alpha S_u \quad (22)$$

where α is the empirical adhesion factor with a value of 1 for normally consolidated clays and 0.5 for over-consolidated ones. Here, undrained shear strength is calculated using $q_{c,av}$ at the corresponding depth. Unit shaft resistance in sand is defined as:

$$q_s = \min \left\{ f_{s,av} , \frac{q_{c,av}}{300} \right\} \quad (23)$$

In this method, unit shaft friction $f_{s,av}$ is limited to 120kPa in sand.

Bustamante and Gianeselli (1982) Method:

This method, which is also called the LCPC or the *French method*, is based on 197 full-scale static pile load tests conducted by the French Highway Department (Bustamante and Gianeselli 1982). According to this method, sleeve friction is neglected and the tip and shaft resistances are obtained from the cone resistance. The unit tip resistance is calculated as:

$$q_p = k_c q_c \quad (24)$$

where k_c is the bearing capacity factor which depends on soil conditions and q_c is measured from 1.5D above the pile tip to 1.5D below the pile tip. Unit shaft friction is determined by:

$$q_s = \frac{q_{c,av}}{k_s} \quad (25)$$

where k_s is a coefficient depending on the pile installation method and material and $q_{c,av}$ is the average cone resistance over the pile length. This method is not specialized for different soil types.

UWA Method:

Lehane et al. (2005) propose a new design method for open ended steel pipe piles driven into sand called UWA method in the University of Western Australia. This method calculates the pile capacity analytically under compressive and tensile loading with two components namely the end bearing capacity and the shaft friction capacity. Only the shaft friction capacity is considered in this study using:

$$Q_s = \pi D \int \tau_f dz \quad (26)$$

where D is outer pile diameter. Here τ_f is the unit shaft resistance and given as,

$$\tau_f = \sigma'_{rf} \tan \delta_{cv} = \frac{f}{f_c} (\sigma'_{rc} + \Delta \sigma'_{rd}) \tan \delta_{cv} \quad (27)$$

where, δ_{cv} is the interface friction angle and $\frac{f}{f_c}$ is a constant term taking values of 1.0 for compression and 0.75 for tension. Effective stress terms σ'_{rc} and $\Delta \sigma'_{rd}$ are the radial effective stress after installation and the change of radial stress due to dilation, respectively. The former is calculated as:

$$\sigma'_{rc} = 0.03 \cdot q_c (A_{rs}^*)^{0.3} \left[\max\left(\frac{h}{D}, 2\right) \right]^{-0.5} \quad (28)$$

where h is the length between the corresponding depth and the pile tip and A_{rs}^* is the effective area function based on IFR, given as:

$$A_{rs}^* = 1 - IFR \left(\frac{D_i}{D} \right)^2 \quad (29)$$

where D_i is the inner diameter of the pile. The change of radial effective stress is given as,

$$\Delta \sigma'_{rd} = 4G \cdot \frac{\Delta r}{D} \quad (30)$$

where Δr is the dilation of particles assumed as 0.02 mm and G is operational shear modulus that is calculated based on q_c values:

$$\frac{G}{q_c} = 185 \cdot \left[\frac{q_c/p_a}{(\sigma'_{v0}/p_a)^{0.5}} \right]^{-0.75} \quad (31)$$

413 *NGI Method:*

414 The NGI method proposed by Norwegian Geotechnical Institute (Clausen et al. 2005) examining 85 pile
415 load tests from 35 different locations is another commonly-used method to predict the shaft capacity of
416 open ended steel pipe piles driven into cohesionless soils. This method suggests a function of the unit
417 skin resistance based on the depth, z :

$$418 \tau_{skin}(z) = z/z_{tip} \cdot \sigma_{atm} \cdot F_{Dr} \cdot F_{sig} \cdot F_{tip} \cdot F_{load} \cdot F_{mat} \quad (32)$$

$$419 \tau_{skin}(z) > 0.1 \cdot \sigma'_{v0} \quad (33)$$

420 where z_{tip} is the depth to pile tip and σ_{atm} is the atmospheric reference pressure. According to method,
421 unit skin resistance should be more than 10 percent of the effective overburden pressure, given in (33).

422 F_{tip} , F_{load} and F_{mat} are the constant coefficients. F_{tip} is taken as 1.0 for driven open-ended piles. F_{load}
423 represents the loading conditions and taken as 1.0 in case of tension. F_{mat} is to define the material effects
424 and taken as 1.0 for steel and F_{Dr} is a function of relative density (D_r) as:

$$425 F_{Dr} = 2.1 \cdot (D_r - 0.1)^{1.7} \quad (34)$$

426 D_r for sands can be calculated by q_c with the equation:

$$427 D_r = 0.4 \cdot \ln \left(\frac{q_c}{22 \cdot (\sigma'_{v0} \cdot \sigma_{atm})^{0.5}} \right) \quad (35)$$

428 Lastly, F_{sig} reflects the effect of overburden pressure by:

$$429 F_{sig} = (\sigma'_{v0} / \sigma_{atm})^{0.25} \quad (36)$$

430 *Fugro Method:*

431 The Fugro-05 design method presents a unit skin friction equation for compression and tension cases,
432 separately (Yang et al. 2015). Tensile loading version is considered in this study as:

$$433 \tau_f = 0.045 \cdot q_c \cdot \left(\frac{\sigma'_{v0}}{\sigma_{atm}} \right)^{0.15} \cdot \left[\max \left(\frac{h}{R^*}, 4 \right) \right]^{-0.85} \quad (37)$$

434 where h is the length between the pile tip and considered depth and R^* is the equivalent pile radius,
435 calculated in terms of the outer and inner radii of the pile:

$$436 R^* = (R_{outer}^2 - R_{inner}^2)^{0.5} \quad (38)$$

5. Results

Nine ML methods discussed previously are applied to CEP and OEP databases, whose results are discussed in this section.

5.1. CEP Database

A large database involving 219 pile load tests with 120 of them having both sleeve friction resistance (f_s) and cone tip resistance (q_c), while 99 of those missing the f_s is generated. The input features in our analyses are determined as the pile length L , its cross-sectional area (A), cone resistance of CPT at the pile tip ($q_{c_{end}}$), sleeve friction along the pile (f_s), and cone resistance along the pile (q_c). The only output is the pile capacity (Q_u), which is entirely the case in this work. Therefore, the first set of analyses are performed on a database of 120 tests that have both q_c and f_s information, and the accuracy of the MLM is estimated based on 5-fold cross validation. Predictions made by the MLM are compared to the actual pile bearing capacities obtained from the pile load test results in terms of R^2 and RE. Here, a comparison is also made between the MLM and that of the classical methods in terms again of the final R^2 and RE values. We will follow a naming convention to avoid confusion and call for instance the first analysis set *120S_5F_9ML* referring to 120 sample, 5 features and 9 MLM.

Based on some preliminary studies on the subject (Shahin 2010), in the second set of analyses, f_s is removed from the feature set, and the analyses are repeated with 120 sample. In addition, 4 of the 9 MLM resulting in the highest correlation with the database are selected and used in the subsequent analyses. This second set is then called *120S_4F_4ML*. It is observed that removing the f_s as a feature enhances the predictive performance of the MLM. Thus, in an attempt to investigate this finding further, the current dataset is expanded with additional 99 pile load test sample without f_s . This enables us to gather a comprehensive database with 219 samples of the pile load test data. In the rest of the analyses called *219S_4F_4ML*, this database is utilized.

The methods are first applied to the initial database including the f_s feature whose results are presented in Table 3. Each row of the table presents R^2 and RE for each fold as applied to each MLM. The highest R^2 and the lowest RE of each method are highlighted in bold. Finally, the performance of each method is assessed based on the statistical values of each analysis, and the results are visualized with boxplots in Figure 3.

According to the results in Table 3, it can be observed that the linear methods are not as efficient as the nonlinear methods, in particular the RF, RVR, GPR, and VHGP methods, which result in relatively high R^2 and low RE. Thus, the boxplot visualization is found useful for identifying the interquartile range and standard deviation obtained in 5-fold cross validation. The height of each box represents the interquartile range of the represented data, meaning that the standard deviation decreases as the size of the box decreases. As can be clearly seen in Figure 3a, average R^2 of RF, RVR, GPR, and VHGP methods (and some others also) are higher than the traditional methods. Also the standard deviations of the R^2 distributions of these methods are considerably less than the traditional methods. The RE distributions, shown in Figure 3b indicate that these four methods predict the axial capacity with less relative error while the classical methods yield a higher error ratio.

Table 3. R^2 and RE calculated for each fold in analysis set *120S_5F_9ML* including classical methods

<i>Fold</i>		<i>RLR</i>	<i>MARS</i>	<i>KNNR</i>	<i>TREE</i>	<i>RF</i>	<i>ELM</i>	<i>RVR</i>	<i>GPR</i>	<i>VHGPR</i>	<i>Schmertmann</i>	<i>DeRuiter</i>	<i>LCPC</i>
1	R^2	0.83	0.85	0.74	0.61	0.86	0.45	0.87	0.85	0.87	0.79	0.74	0.81
	RE	0.39	0.31	0.53	0.40	0.27	0.56	0.27	0.25	0.34	0.28	0.32	0.29
2	R^2	0.71	0.81	0.66	0.60	0.85	0.76	0.80	0.86	0.84	0.80	0.52	0.87
	RE	0.37	0.32	0.52	0.42	0.30	0.38	0.29	0.27	0.30	0.40	0.59	0.34
3	R^2	0.78	0.75	0.76	0.80	0.75	0.77	0.81	0.76	0.76	0.48	0.62	0.58
	RE	0.29	0.39	0.26	0.31	0.29	0.32	0.28	0.34	0.34	0.48	0.46	0.39
4	R^2	0.88	0.79	0.79	0.70	0.89	0.88	0.91	0.89	0.89	0.72	0.74	0.84
	RE	0.22	0.39	0.26	0.36	0.25	0.24	0.30	0.28	0.23	0.75	0.50	0.26
5	R^2	0.73	0.73	0.70	0.29	0.67	0.73	0.82	0.82	0.82	0.58	0.67	0.75
	RE	0.38	0.30	0.32	0.62	0.34	0.38	0.26	0.25	0.25	0.49	0.42	0.30
Mean	R^2	0.787	0.788	0.728	0.601	0.804	0.720	0.842	0.836	0.837	0.675	0.657	0.771
	RE	0.330	0.343	0.379	0.419	0.291	0.374	0.280	0.276	0.291	0.481	0.458	0.315

Predicted pile capacities with Schmertmann and de Ruiter's methods yield less accurate results compared to the static load tests with lower R^2 and higher RE. The LCPC method gives relatively more reliable results, although its algorithm is not as effective as the MLM. The RVR method shows the highest prediction with the mean R^2 value of 0.842, and the GPR and the VHGP are other methods that produce fairly good predictions with a relatively high R^2 value of 0.84. The RF can be considered

as the one with a relatively acceptable prediction. Based on these results, we decide not to consider the remaining MLM in the rest of the analyses due to their poor performances.

Figure 3. Distribution of statistical measures among the ML methods and traditional methods in *120S_5F_9ML*, (a) R^2 , (b) RE

The analyses are subsequently repeated with the same database with only 4 features of L , A , $(q_c)_{end}$, and $(q_c)_{ave}$. No change is made in the 5-folds or in the order of the datasets. The results of four MLM along with the traditional methods are given in Table 4. According to the results, the predictive performances of all the selected MLM increase in comparison to the previous analysis. However, the most apparent change in the R^2 is observed in the RVR method. The mean R^2 value of the RVR becomes 0.87 while the RE is reduced to 0.27. Therefore, it can be concluded that the sleeve friction does not significantly affect the results through the RF, GPR, and VHGP methods except for the RVR. From foundation engineering standpoint, we find this result somewhat interesting, in that the sleeve friction, although an important parameter in predicting pile load capacity, is not highly correlated with the Q_u based on the nonlinear methods used in this study, which seems to be supporting an earlier claim on the matter (Shahin 2010). Summarized boxplots are shown in Figure 4. As can be seen in Figure 4, the standard deviations obtained by the 4 MLM are less than the ones by the classical methods meaning that more robust results are obtained.

Table 4. R^2 and RE for the selected MLM and classical methods in the *120S_4F_4ML* set

<i>Fold</i>		<i>RF</i>	<i>RVR</i>	<i>GPR</i>	<i>VHGP</i>	<i>Schmertmann</i>	<i>DeRuiter</i>	<i>LCPC</i>
1	R^2	0.86	0.87	0.85	0.88	0.79	0.74	0.81
	RE	0.27	0.24	0.26	0.32	0.28	0.32	0.29
2	R^2	0.87	0.91	0.87	0.85	0.80	0.52	0.87
	RE	0.28	0.25	0.26	0.30	0.40	0.59	0.34
3	R^2	0.75	0.80	0.75	0.76	0.48	0.62	0.58
	RE	0.31	0.29	0.34	0.33	0.48	0.46	0.39
4	R^2	0.88	0.91	0.90	0.88	0.72	0.74	0.84
	RE	0.24	0.30	0.29	0.27	0.75	0.50	0.26
5	R^2	0.70	0.84	0.85	0.81	0.58	0.67	0.75
	RE	0.32	0.26	0.22	0.25	0.49	0.42	0.30
Mean	R^2	0.81	0.87	0.84	0.84	0.67	0.66	0.77
	RE	0.29	0.27	0.28	0.29	0.48	0.46	0.31

With the aim of understanding this outcome, we have further extended our database with 99 more pile load tests from the literature resulting in a total of 219 test results in the database with the same 4 features. Firstly, a 5-fold analysis on the new database is made as a trial run yielding unsatisfactory results. Secondly, a 10-fold cross-validation method with 10 different data groups is applied on the new database aiming more accuracy and validity. However, the accuracy does not increase as much as desired.

Following this third analysis, now named *219S_4F_4ML*, the results are compared for R^2 and RE distributions in Table 5, and its boxplot given in Figure 5. The results show that the ML performances somewhat decrease in this new dataset. While there is a rise in the scatter of data obtained from different sources in the literature that may have created some inconsistency among them, this may also be attributed to the absence of f_s . That is, although poorly correlated with Q_u through the data-driven models, such a mechanics-wise important parameter in geotechnical engineering practice is not easy to discard in the prediction of Q_u of closed-ended piles irrespective of the MLM used. Having said that, the RF method still demonstrates its robustness with an acceptable predictive performance of a mean R^2 of 0.84. According to the results, it is fair to say that given the relatively large database, the RF can be identified as MLM with the best capability of predicting pile load capacity compared to both the traditional methods and other nonlinear MLM. However, one can argue that as the database is extended with more consistent data, other three nonlinear MLM; RVR, GPR and VHGP might improve.

Figure 4. Distribution of statistical parameters among the MLM and traditional methods in *120S_4F_4ML*, (a) R^2 , (b) RE

Figure 5. Boxplot visualization of the *219S_4F_4ML* analysis set, (a) R^2 , (b) RE

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Table 5. R^2 and RE values of the *219S_4F_4ML* analysis set

<i>Fold</i>		<i>RF</i>	<i>RVR</i>	<i>GPR</i>	<i>VHGPR</i>	<i>Schmertmann</i>	<i>DeRuiter</i>	<i>LCPC</i>
1	R²	0.81	0.62	0.77	0.76	0.82	0.57	0.80
	RE	0.28	0.44	0.31	0.33	1.15	0.93	0.29
2	R²	0.87	0.88	0.63	0.84	0.61	0.64	0.92
	RE	0.24	0.22	0.52	0.27	0.67	0.53	0.20
3	R²	0.77	0.63	0.63	0.68	0.52	0.78	0.72
	RE	0.33	0.43	0.41	0.38	1.47	0.40	0.37
4	R²	0.90	0.86	0.89	0.88	0.70	0.71	0.88
	RE	0.22	0.26	0.24	0.25	1.28	0.66	0.30
5	R²	0.85	0.70	0.32	0.71	0.56	0.71	0.74
	RE	0.24	0.40	0.50	0.40	0.44	0.67	0.33
6	R²	0.72	0.58	0.52	0.68	0.40	0.36	0.84
	RE	0.50	0.63	0.65	0.51	1.22	1.22	0.26
7	R²	0.84	0.80	0.73	0.72	0.86	0.66	0.80
	RE	0.32	0.34	0.42	0.42	0.29	0.51	0.35
8	R²	0.95	0.96	0.96	0.96	0.94	0.97	0.93
	RE	0.17	0.20	0.15	0.15	0.39	0.23	0.25
9	R²	0.90	0.62	0.64	0.72	0.97	0.95	0.90
	RE	0.49	0.61	0.58	0.55	1.15	0.88	0.28
10	R²	0.79	0.85	0.88	0.82	0.66	0.55	0.74
	RE	0.27	0.24	0.21	0.26	0.39	0.50	0.36
Mean	R²	0.84	0.75	0.70	0.78	0.70	0.69	0.83
	RE	0.31	0.38	0.40	0.35	0.84	0.65	0.30

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533 **5.2. OEP Database**

534 The second database contains 60 tensile tests applied on open-ended steel pipe piles embedded in
535 cohesionless soils. The input features and the output are presented in Table 2. The analysis of the OEP
536 database is performed on two sets of data. Firstly, the shaft capacity of all piles in the OEP database are
537 predicted with MLM, and the performance of MLM and conventional methods are compared. Then the
538 outlier piles with a relatively larger capacity are eliminated to provide consistency among the data, which
539 are now 49. Using the same naming convention as before, the first analysis including all collected data
540 is called *60S_5F_9ML*, and the second *49S_5F_9ML*. The results of the first analysis are given in Table
541 6 and its boxplot graph is in Figure 6.

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Table 6. R^2 and RE values of the *60S_5F_9ML* analysis set

<i>Fold</i>		<i>RLR</i>	<i>MARS</i>	<i>KNNR</i>	<i>TREE</i>	<i>RF</i>	<i>ELM</i>	<i>RVR</i>	<i>GPR</i>	<i>VHGPR</i>	<i>UWA</i>	<i>NGI</i>	<i>Fugro</i>
1	R²	0.72	0.90	0.75	0.72	0.91	0.90	0.96	0.94	0.79	0.96	0.96	0.89
	RE	0.55	0.64	0.48	0.86	0.45	0.53	0.57	0.61	0.63	0.18	0.21	0.21
2	R²	0.54	0.25	0.85	0.02	0.76	0.68	0.98	0.40	0.86	0.98	0.99	0.84
	RE	0.64	2.05	0.64	1.43	0.49	0.54	0.30	0.69	0.43	0.37	0.24	0.24
3	R²	0.95	0.94	0.99	0.48	0.88	0.95	0.93	0.96	0.50	0.89	0.92	0.60
	RE	0.26	0.21	0.20	0.74	0.39	0.26	0.29	0.21	0.73	0.44	0.30	0.30
4	R²	0.91	1.00	0.94	0.93	0.99	0.94	0.95	0.98	0.94	0.92	0.95	0.78
	RE	0.51	0.35	0.61	0.58	0.37	0.45	0.42	0.38	0.67	0.50	0.38	0.38
5	R²	0.60	0.24	0.66	0.09	0.23	0.61	0.98	0.85	0.71	0.89	0.81	0.83
	RE	0.58	0.78	0.94	1.31	0.92	0.57	0.15	0.32	0.58	0.28	0.38	0.38
Mean	R²	0.74	0.67	0.84	0.45	0.76	0.81	0.96	0.83	0.76	0.93	0.92	0.79
	RE	0.51	0.81	0.57	0.98	0.52	0.47	0.34	0.44	0.61	0.35	0.30	0.30

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Figure 6. Boxplot visualization of the *60S_5F_9ML* analysis set, (a) R^2 , (b) RE.

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The results show that the KNNR, ELM, RVR and GPR methods provide more consistent predictions than the other MLM. RVR gives the best prediction in terms of mean R^2 and RE. Comparing the MLM with the conventional methods, it is clear that the conventional ones, the UWA and NGI methods, show a fairly better performance than all of the MLM except RVR with a mean R^2 of 0.96. This shows a very good correlation between the predicted friction capacities and the measured ones in the load tests. There is a significant difference between RVR and the Fugro method while it is closer in R^2 values to the UWA and NGI methods. Results also show that the mean RE value of 0.34 of the RVR method is compatible with the conventional methods. Besides, as per Figure 6, the standard deviation of the R^2 values is less than the other MLM and the conventional ones. Thus, our results indicate that RVR provides the best prediction for *60S_5F_9ML* analysis.

The second set of data used in *49S_5F_9ML* analysis is prepared by eliminating 11 pile test data with long and large diameter piles since these piles have considerably large shaft capacities causing an outlier behavior. The results of the analysis are given in Table 7 and the boxplot graph can be seen in Figure 7.

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Table 7. R^2 and RE values of the *49S_5F_9ML* analysis set

<i>Fold</i>		<i>RLR</i>	<i>MARS</i>	<i>KNNR</i>	<i>TREE</i>	<i>RF</i>	<i>ELM</i>	<i>RVR</i>	<i>GPR</i>	<i>VHGPR</i>	<i>UWA</i>	<i>NGI</i>	<i>Fugro</i>
1	R²	0.88	0.90	0.76	0.89	0.92	0.34	0.93	0.89	0.96	0.82	0.76	0.56
	RE	0.29	0.25	0.36	0.35	0.22	0.82	0.28	0.28	0.18	0.30	0.36	0.36
2	R²	0.77	0.79	0.60	0.84	0.88	0.77	0.65	0.85	0.83	0.75	0.76	0.60
	RE	0.26	0.25	0.33	0.34	0.18	0.24	0.30	0.19	0.21	0.36	0.38	0.38
3	R²	0.83	0.93	0.90	0.58	0.73	0.92	0.76	0.83	0.87	0.75	0.67	0.82
	RE	0.37	0.22	0.29	0.44	0.39	0.37	0.39	0.35	0.35	0.59	0.91	0.91
4	R²	0.89	0.98	0.83	0.90	0.98	0.89	0.85	0.97	0.96	0.83	0.78	0.69
	RE	0.26	0.12	0.35	0.27	0.20	0.27	0.28	0.14	0.14	0.30	0.34	0.34
5	R²	0.67	0.81	0.89	0.87	0.88	0.75	0.91	0.84	0.84	0.67	0.55	0.56
	RE	0.46	0.34	0.30	0.31	0.29	0.41	0.35	0.32	0.32	0.45	0.54	0.54
Mean	R²	0.81	0.88	0.80	0.82	0.88	0.73	0.82	0.87	0.89	0.77	0.70	0.64
	RE	0.33	0.24	0.33	0.34	0.25	0.42	0.32	0.26	0.24	0.40	0.51	0.51

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564 **Figure 7.** Boxplot visualization of the *49S_5F_9ML* analysis set, (a) R^2 , (b) RE

565 After eliminating the outlier piles, the predictive performances of the UWA, NGI and Fugro methods
566 dramatically decrease, which can be concluded that these methods work somewhat better in predicting
567 the large diameter piles with higher shaft capacity. Also, MLM have higher R^2 and lower RE values in
568 this analysis. The mean R^2 values for MARS, RF, GPR and VHGPR methods are higher than the other
569 MLM and conventional methods with lower RE values. VHGPR method provides the best prediction
570 for the *49S_5F_9ML* analysis with a higher mean R^2 of 0.89 and lower mean RE of 0.24.

571 5.3. Model Verification

572 The scatter of actual pile load test results versus the predicted results achieved by the MLM as well as
573 the classical methods are compared in this section. In the analysis of CEP database, it should be
574 mentioned that although *219S_4F_4ML* set results in the highest R^2 of 0.96 for a specific fold in the
575 latest analysis (Table 5), since the mean values are not increased significantly in the expanded database
576 we focus our attention back on the second set of analysis with *120S_4F_4ML* which seems to present a
577 more consistent dataset herein. Thus, Figure 8 presents the actual pile capacities versus the predictions

for all folds in this second round of analysis. The best performance of the MLM is observed when folds 1, 2, 3, and 5 are used for training, and fold 4 is used for testing. Therefore, the RVR method gives the highest R^2 value of 0.91 and the lowest RE of 0.27 showing that this method presents a better performance than the classical methods. Figure 9 shows predicted versus measured pile capacity graphs in this case. Also, the regression graph of RVR compared to the classical methods is given in Figure 10.

Figure 8. Regression graphs of *120S_4F_4ML*, (a) RF, (b) GPR, (c) RVR, (d) VHGP, (All folds are used as testing data)

In the OEP analysis, RVR shows a much better predictive performance with the highest R^2 of 0.96 in the case of *60S_5F_5ML*. In the *49S_5F_5ML* analysis, MLM provide a stronger correlation than classical methods. Therefore, we focus our attention on *49S_5F_5ML* analysis to compare MLM with the classical methods. MARS, RF, GPR and VHGP stand out due to their relatively high mean R^2 and low mean RE. Figure 11 shows the actual shaft capacities of piles with respect to the predicted values for all folds. The VHGP method produces the best predictions with 0.89 R^2 and 0.24 RE. Especially the predictions of VHGP are too close to the actual capacities when folds 1, 2, 3, and 5 are used for training. Regression plots are given in Figure 12.

Figure 9. Regression graphs of ML methods and traditional methods

Figure 10. Regression graph of RVR method compared with traditional methods, ($R^2 = 0.91$ for RVR, 0.72 for Schmertmann, 0.74 for DeRuiter, and 0.84 for LCPC)

Figure 11. Regression graphs of *49S_5F_9ML*, (a) MARS, (b) RF, (c) GPR, (d) VHGP, (All folds are used as testing data)

Figure 12. Regression graph of VHGP method compared with traditional methods, ($R^2 = 0.96$ for RVR, 0.83 for UWA, 0.78 for NGI, and 0.69 for Fugro)

5 Conclusion

In this study, static load bearing capacities of closed- and open-ended piles in both cohesive and cohesionless soils are predicted using machine learning. Nine of such most common methods are comparatively used for that matter. A comprehensive database is generated for the closed-ended piles, and a moderate database is gathered for the open-ended piles based on static pile load tests and cone penetration tests. These databases are then used to teach these algorithms in terms of five features associated with the pile geometry and CPT data. Results indicate that generally nonlinear methods perform better than the linear ones particularly the RF, RVR, GPR, and VHGP methods. Among these four methods, the Relevance Vector Regression (RVR) performs well for the closed-ended piles and the VHGP predicts well for the open-ended piles compared to both the classical empirical methods and the other nonlinear machine learning methods. The Random Forest (RF) method can be considered as the one with the most capability of accurately predicting the friction capacity of both types of piles. Thus, we conclude that given a large enough database, it is possible to predict the static pile load capacity of both closed- and open-ended piles in both cohesive and cohesionless soils with sufficient accuracy, particularly when a specific set of machine learning methods is used.

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Reference	Cone Type	Pile No	Installation Type	Pile Type	Material	Length (m)	Area (m ²)	(q _c) _{end} (MPa)	(q _c) _{ave} (MPa)	(f _s) _{ave} (MPa)	Q _u (kN)
(Altaee et al. 1992)	M	BGHD1	D	SP	C	11.0	0.0812	3.050	3.213	0.051	1000
(Altaee et al. 1992)	M	BGHD2	D	SP	C	15.0	0.0812	7.060	4.861	0.058	1600
(Eslami 1996)	E	POLA1	D	OC	C	25.8	0.3080	16.461	6.973	0.085	5785
(Eslami 1996)	E	TWNT4	D	CP	S	34.2	0.2913	7.613	3.372	0.028	4330
(Eslami 1996)	E	TWNT6	D	CP	S	34.2	0.2913	7.537	4.341	0.036	4460
(Tumay and Fakhroo 1981)	E	LSUA1	D	SP	C	9.5	0.1225	1.359	6.937	0.099	900
(Tumay and Fakhroo 1981)	E	LSUB12	D	CP	C	37.8	0.6362	1.977	2.278	0.027	3960
(Tumay and Fakhroo 1981)	E	LSUN11	D	SP	C	36.5	0.2025	2.768	1.328	0.015	2950
(Tumay and Fakhroo 1981)	E	LSUN15	D	CP	S	37.5	0.1257	3.220	1.364	0.014	2800
(Tumay and Fakhroo 1981)	E	LSUN28	D	T	C	30.5	0.1075	3.134	0.787	0.014	2160
(Tumay and Fakhroo 1981)	E	LSUN215	D	CP	S	31.1	0.0962	3.930	0.819	0.014	1710
(Tumay and Fakhroo 1981)	E	LSUN216	D	CP	S	41.8	0.1257	1.916	1.265	0.017	1890
(Eslami 1996)	E	UFL22	D	SP	C	16.0	0.1225	6.776	6.175	0.128	1350
(Eslami 1996)	E	UFL52	D	SP	C	11.0	0.2500	5.881	13.030	0.072	2070
(Eslami 1996)	E	UFL53	D	SP	C	20.4	0.1225	5.428	5.101	0.067	1260
(Eslami 1996)	M	LTN741	B	CP	C	25.8	0.5153	12.096	8.411	0.113	7830
(Eslami 1996)	E	LTN742	B	CP	C	24.1	0.5153	8.493	7.564	0.225	5850
(Eslami 1996)	E	MILANO	D	CP	S	10.0	0.0855	2.866	3.166	0.036	625
(Eslami 1996)	E	OKLACO	D	CP	C	18.2	0.2922	9.487	9.523	0.045	3600
(Eslami 1996)	E	OKLAST	D	CP	S	18.2	0.3421	9.375	9.279	0.048	3650
(Eslami 1996)	E	L&D31	D	CP	S	16.2	0.0707	20.189	16.678	0.064	1310
(Eslami 1996)	E	L&D34	D	CP	S	14.4	0.0962	19.813	16.473	0.058	1300
(Eslami 1996)	E	L&D37	D	CP	S	14.6	0.1257	19.000	16.564	0.062	1800
(Horvitz et al. 1986)	E	SEATW	B	CP	C	15.8	0.0962	3.104	3.044	0.043	900
(Eslami 1996)	E	GIT1	B	CP	C	16.8	0.4418	5.691	5.184	0.104	4500

(Eslami 1996)	E	A&N1	D	SP	C	14.0	0.2025	9.390	5.953	0.077	3850
(Eslami 1996)	E	A&N2	D	SP	C	13.7	0.2025	8.204	5.509	0.078	4250
(Eslami 1996)	E	USPB1	B	CP	C	9.4	0.0962	2.586	1.391	0.052	645
(Eslami 1996)	E	USPB2	B	CP	C	9.4	0.1257	2.262	1.282	0.055	725
(Tumay and Fakhroo 1981)	E	LSUH1	D	SP	C	29.0	0.2025	1.412	0.990	0.014	1935
(Tumay and Fakhroo 1981)	E	LSUR24	D	SP	C	19.8	0.3600	2.127	1.141	0.027	2025
(Tumay and Fakhroo 1981)	E	LSUR30	D	SP	C	19.8	0.5625	2.007	1.113	0.028	2610
(Eslami 1996)	M	NETH2	D	SP	C	9.25	0.0625	2.663	0.734	0.005	700
(Eslami 1996)	E	UHUC1	D	CP	S	13.0	0.0590	4.064	2.251	0.033	780
(Eslami 1996)	E	UHUC11	D	CP	S	13.0	0.0590	3.825	2.695	0.061	800
(Ebrahimian and Movahed 2017)	E	Case 1	D	CP	S	17.4	0.0995	7.500	2.711	0.062	1880
(Eslami 1996)	E	UBC2	D	CP	S	13.7	0.0824	0.569	0.425	0.009	290
(Eslami 1996)	E	UBC3	D	CP	S	16.8	0.0824	5.044	0.830	0.012	630
(Eslami 1996)	E	UBC5	D	CP	S	31.1	0.0824	3.058	2.311	0.024	1100
(Finno 1989)	E	NWUP	D	CP	S	15.2	0.1590	0.776	4.545	0.068	1020
(Eslami 1996)	E	FHWASF	D	CP	S	9.2	0.0585	6.050	5.231	0.013	490
(Eslami 1996)	E	LTN484	B	CP	C	7.6	0.1590	2.205	2.510	0.073	750
(Eslami 1996)	E	MUMB	D	CP	S	12.2	0.0585	16.480	9.554	0.068	1686
(Eslami 1996)	E	A&N3	D	CP	C	10.2	0.0990	7.723	4.123	0.038	1300
(Eslami 1996)	M	N&SWP1	D	SP	C	8	0.2025	2.661	2.328	0.021	1140
(Eslami 1996)	M	N&SWP2	D	SP	C	11.3	0.2025	1.730	2.066	0.017	830
(Eslami 1996)	M	N&SJC1	D	SP	C	9.15	0.2025	11.333	13.245	0.127	1845
(Eslami 1996)	M	N&S215	D	SP	C	21.3	0.0625	4.806	4.482	0.030	810
(Eslami 1996)	M	N&S316	D	SP	C	15.85	0.1225	4.719	3.457	0.027	1485
(Eslami 1996)	M	N&SBI42	D	CP	S	15.2	0.0585	3.752	3.533	0.030	675
(Eslami 1996)	M	N&SBI43	D	CP	S	22.5	0.0585	13.533	6.804	0.042	1620
(Eslami 1996)	M	N&S348	D	SP	C	14.9	0.2025	4.524	4.972	0.034	1755
(Eslami 1996)	E	PRS	D	CP	S	28.4	0.0707	1.286	2.024	0.027	1240
(Eslami 1996)	E	PRL	D	CP	S	31.4	0.0707	1.389	2.341	0.022	1690

(Eslami 1996)	M	A&M5	D	SP	C	8.5	0.2025	2.336	2.294	0.062	1330
(Eslami 1996)	M	A&M6	D	SP	C	6.5	0.1225	4.373	3.420	0.082	800
(Eslami 1996)	M	A&M7	D	SP	C	6.7	0.1225	3.671	3.047	0.067	1470
(Eslami 1996)	M	A&M8	D	SP	C	7.6	0.2025	8.969	6.110	0.099	1070
(Eslami 1996)	M	A&M19	D	SP	C	8.4	0.1600	6.632	1.858	0.026	1240
(Eslami 1996)	M	A&M20	D	SP	C	21	0.1600	6.301	1.570	0.015	1330
(Eslami 1996)	M	A&M22	D	SP	C	10.3	0.2025	4.043	2.192	0.030	1250
(Eslami 1996)	M	A&M24	D	SP	C	13.4	0.1600	7.096	3.133	0.043	1170
(Eslami 1996)	M	A&M26	D	SP	C	8.6	0.1225	4.349	3.112	0.020	600
(Eslami 1996)	M	A&M30	D	SP	C	15	0.2025	7.582	4.445	0.062	1420
(Eslami 1996)	M	A&M31	D	SP	C	10.4	0.2025	2.346	2.695	0.048	1070
(Eslami 1996)	M	A&M32	B	CP	C	10.6	0.0962	9.106	5.819	0.083	1160
(Eslami 1996)	M	A&M33	B	CP	C	8.9	0.0962	8.827	6.679	0.099	1170
(Eslami 1996)	M	A&M34	B	CP	C	6.5	0.0962	10.306	5.716	0.081	880
(Eslami 1996)	M	A&M35	D	SP	C	10.4	0.1600	5.560	2.288	0.042	1170
(Eslami 1996)	M	A&M36	B	CP	C	8.5	0.0962	5.483	3.107	0.059	720
(Eslami 1996)	M	A&M38	D	SP	C	11.3	0.1600	5.004	3.594	0.074	870
(Eslami 1996)	M	A&M40	D	SP	C	16	0.1225	6.195	6.238	0.059	1070
(Eslami 1996)	M	A&M46	D	SP	C	11.4	0.1600	7.710	5.003	0.057	1140
(Eslami 1996)	M	A&M47	D	SP	C	11.2	0.1600	7.688	8.656	0.056	1020
(Eslami 1996)	M	A&M48	D	SP	C	12.5	0.1600	3.325	3.105	0.029	620
(Eslami 1996)	M	A&M49	D	SP	C	12.5	0.1600	3.661	3.080	0.028	1170
(Eslami 1996)	M	A&M66	D	SP	C	25	0.1225	6.480	5.895	0.063	1560
(Eslami 1996)	M	A&M69	D	SP	C	19.2	0.1600	0.790	1.244	0.019	1780
(Eslami 1996)	M	A&M79	B	CP	C	11.5	0.0707	7.351	4.201	0.099	1320
(Eslami 1996)	M	A&M86	B	CP	C	10.7	0.0962	7.382	3.196	0.045	1390
(Eslami 1996)	M	A&M87	D	SP	C	7.4	0.1600	2.969	1.749	0.034	640
(Eslami 1996)	M	A&M90	D	SP	C	10.7	0.2025	4.851	1.872	0.040	1500
(Eslami 1996)	M	A&M1	D	SP	C	8.8	0.1600	8.198	3.396	0.031	1140
(Eslami 1996)	M	A&M4	B	CP	C	12.5	0.0962	6.892	3.008	0.043	1100
(Yang et al. 2015)	E	PJ PI-1	D	SP	C	37.2	0.2500	24.937	6.272	0.036	3590

(Yang et al. 2015)	E	RJ PI-2	D	SP	C	21.4	0.2500	14.362	4.493	0.024	1950
(Yang et al. 2015)	E	RJ PI-4	D	SP	C	26.5	0.2500	11.778	5.060	0.026	4532
(Naesgaard et al. 2012)	E	BC P1	D	CP	S	45	0.2922	9.581	4.259	0.054	3750
(Yang et al. 2015)	M	HRV P1	D	SP	C	16.8	0.3721	6.619	6.222	0.030	3095
(Yang et al. 2015)	M	BR 2108	D	SP	C	7.6	0.2116	14.080	6.089	0.070	1601
(Yang et al. 2015)	M	BR 3028	D	SP	C	7.6	0.2116	8.088	1.822	0.020	1425
(Yang et al. 2015)	M	BR 3118A	D	SP	C	7.6	0.1681	2.893	5.517	0.082	750
(Yang et al. 2015)	M	BR 3123B	D	SP	C	16.6	0.1296	5.865	6.214	0.069	1100
(Yang et al. 2015)	M	BR 3142A	D	SP	C	6.18	0.1296	17.449	6.493	0.072	850
(Kalavar and Ealy 2000)	M	11	DS	CP	C	8.4	0.1295	8.624	11.941	0.081	1160
(Kalavar and Ealy 2000)	M	12	DS	CP	C	9.3	0.1295	8.945	11.190	0.079	1445
(Kalavar and Ealy 2000)	M	1	DS	CP	C	10.7	0.1219	8.100	3.855	0.017	1460
(Kalavar and Ealy 2000)	M	2	DS	CP	C	8.1	0.1295	11.906	7.478	0.096	1044
(Kalavar and Ealy 2000)	M	3	DS	CP	C	8.4	0.1295	20.018	12.447	0.070	1109
(Kalavar and Ealy 2000)	M	4	DS	CP	C	5.6	0.1295	12.309	9.541	0.069	624
(Kalavar and Ealy 2000)	M	5	DS	CP	C	7.9	0.1295	11.854	16.833	0.087	666
(Kalavar and Ealy 2000)	M	6	DS	CP	C	7.6	0.1219	6.846	3.932	0.051	1014
(Kalavar and Ealy 2000)	M	7	DS	CP	C	6.5	0.1219	6.886	16.529	0.151	813
(Kalavar and Ealy 2000)	M	8	DS	CP	C	6.6	0.1295	8.051	7.224	0.146	1234
(Kalavar and Ealy 2000)	M	9	DS	CP	C	7	0.1295	8.632	15.233	0.112	1320
(Kalavar and Ealy 2000)	M	10	DS	CP	C	10.4	0.1295	8.246	11.220	0.091	1150
(Kalavar and Ealy 2000)	M	1066	DS	CP	C	14.9	0.0995	9.447	3.657	0.052	1246
(Kalavar and Ealy 2000)	M	1073	DS	CP	C	11.9	0.0731	7.470	4.239	0.101	1744
(Kalavar and Ealy 2000)	M	3042	DS	CP	C	13.8	0.0995	10.564	6.763	0.097	1314
(Kalavar and Ealy 2000)	M	3043	DS	CP	C	12.7	0.0995	9.927	7.255	0.111	1221
(Kalavar and Ealy 2000)	M	3044	DS	CP	C	12.7	0.0995	9.952	3.892	0.054	1350
(Kalavar and Ealy 2000)	M	3045	DS	CP	C	9.6	0.0995	18.252	8.635	0.125	1023
(Kalavar and Ealy 2000)	M	3047	DS	CP	C	10.6	0.0995	7.157	3.641	0.067	771
(Abu-Farsakh et al. 1999)	E	TP7	D	SP	C	36.576	0.5806	2.276	0.554	0.015	5395
(Briaud et al. 2000)	E	Pile 4	B	CP	C	11.5	0.6576	9.144	8.540	0.133	4004
(Briaud et al. 2000)	E	Pile 7	B	CP	C	11	0.6576	5.430	3.393	0.161	3025

(Brown et al. 2006)	E	MLT	B	CP	C	12.1	0.2827	1.782	1.711	0.073	1800
(Fellenius et al. 2004)	E	FL	D	CP	S	45	0.1295	0.848	0.626	0.007	1915
(Fellenius et al. 2007)	E	C1	D	SP	C	6	0.1225	5.196	4.263	0.200	1500
(Paik et al. 2003)	E	PS	D	CP	S	8.24	0.0995	1.885	7.531	0.047	1499
(Yang et al. 2015)	E	RH-P6	D	SP	C	30.6	0.1444	29.846	13.078	N/A	4320
(Yang et al. 2015)	E	RH-P8	D	SP	C	30.3	0.1444	29.826	12.974	N/A	4450
(Yang et al. 2015)	E	RH-P10	D	SP	C	30.7	0.1444	29.846	13.078	N/A	4330
(Yang et al. 2015)	E	WDD P2	D	SP	C	10	0.1225	9.008	0.845	N/A	1150
(Yang et al. 2015)	E	JCEPF 2	D	CP	S	17.8	0.0585	12.304	5.333	N/A	1088
(Yang et al. 2015)	E	TH52 MAT2	D	CP	S	20.29	0.0995	10.819	7.224	N/A	2230
(Yang et al. 2015)	M	H-2	D	SP	C	15.2	0.1648	17.027	9.635	N/A	2750
(Yang et al. 2015)	M	H-12	D	CP	S	6.1	0.1640	10.528	6.280	N/A	2080
(Yang et al. 2015)	M	H-13	D	CP	S	8.9	0.1640	13.638	8.824	N/A	2640
(Yang et al. 2015)	M	H-14	D	CP	S	12	0.1640	10.808	8.773	N/A	3210
(Yang et al. 2015)	M	H-15	D	CP	S	15	0.1640	15.213	10.017	N/A	3950
(Yang et al. 2015)	M	A	D	CP	C	8	0.0616	2.277	2.767	N/A	280
(Yang et al. 2015)	M	D/A	D	CP	C	16	0.0616	4.772	3.053	N/A	490
(Yang et al. 2015)	M	E-7.5	D	CP	C	7.5	0.0616	2.205	2.805	N/A	210
(Yang et al. 2015)	M	E-11.5	D	CP	C	11.5	0.0616	3.055	2.777	N/A	330
(Yang et al. 2015)	M	E-15.5	D	CP	C	15.5	0.0616	4.516	3.016	N/A	470
(Yang et al. 2015)	M	E-19.5	D	CP	C	19.5	0.0616	7.843	3.442	N/A	640
(Yang et al. 2015)	M	E-23.5	D	CP	C	23.5	0.0616	8.394	3.777	N/A	840
(Yang et al. 2015)	M	2-C	D	CP	S	6.8	0.0995	65.954	24.638	N/A	2850
(Briaud and Tucker 1989)	E	3-1	D	CP	S	14.2	0.0731	24.535	17.415	N/A	1170
(Briaud and Tucker 1989)	E	3-4	D	CP	S	14.4	0.0995	23.953	17.603	N/A	1150
(Briaud and Tucker 1989)	E	3-7	D	CP	S	14.6	0.1295	22.710	17.781	N/A	1620
(Yang et al. 2015)	M	P23	D	SP	C	16.8	0.0552	15.192	5.508	N/A	1720
(Yang et al. 2015)	M	P25	D	SP	C	17.8	0.0552	17.326	5.964	N/A	1650
(Yang et al. 2015)	M	P26	D	SP	C	16.2	0.0756	12.275	5.318	N/A	1360
(Yang et al. 2015)	E	D-5	D	SP	C	12.8	0.0552	3.914	2.786	N/A	340

(Yang et al. 2015)	E	D-1	D	SP	C	13	0.0552	4.244	2.817	N/A	310
(Eslami 1996)	E	S	D	CP	S	35.9	0.2027	16.031	3.865	N/A	5490
(Eslami 1996)	E	SPB	B	CP	C	8.7	0.1963	8.538	4.390	N/A	3000
(Eslami 1996)	M	YOG1	D	CP	C	12	0.2124	0.168	0.382	N/A	430
(Eslami 1996)	M	YOG2	D	CP	C	14.5	0.2124	0.495	0.775	N/A	700
(Eslami 1996)	M	KLO14A	B	CP	C	12	0.2827	21.736	4.785	N/A	5500
(Eslami 1996)	M	KLO14B	B	CP	C	12	0.2827	21.697	5.181	N/A	6100
(Eslami 1996)	E	LTN 930	B	CP	C	6.5	0.1257	8.240	7.780	N/A	1385
(Eslami 1996)	E	LTN 938	B	CP	C	9.3	0.1257	11.512	10.806	N/A	1370
(Eslami 1996)	E	PTSER	D	CP	C	33.5	0.2011	13.142	2.712	N/A	5500
(Eslami 1996)	E	PT361	D	CP	C	43	0.2011	10.732	1.466	N/A	6000
(Alsamman 1995)	M	LTN 17	DS	CP	C	7.0	0.4560	2.850	2.754	N/A	1281
(Alsamman 1995)	M	LTN 19	DS	CP	C	7.0	0.4560	2.818	2.759	N/A	1076
(Alsamman 1995)	M	LTN 20	DS	CP	C	13.7	0.4560	4.542	3.478	N/A	2807
(Alsamman 1995)	M	LTN 33	DS	CP	C	10.2	0.6094	3.686	2.109	N/A	1957
(Alsamman 1995)	M	LTN 35	DS	CP	C	12.9	1.3242	3.271	3.271	N/A	5783
(Alsamman 1995)	M	LTN 37	DS	CP	C	10.0	2.5399	1.171	3.477	N/A	8896
(Alsamman 1995)	M	LTN 858	DS	CP	C	27.4	0.5518	14.045	9.700	N/A	8007
(Alsamman 1995)	M	LTN 913	DS	CP	C	12.5	0.0999	5.972	2.563	N/A	983
(Alsamman 1995)	M	LTN 914	DS	CP	C	10.6	0.0999	7.984	5.079	N/A	1010
(Alsamman 1995)	M	LTN 915	DS	CP	C	8.9	0.0999	7.549	5.844	N/A	1068
(Alsamman 1995)	M	LTN 916	DS	CP	C	6.7	0.0999	9.537	5.250	N/A	801
(Alsamman 1995)	M	LTN 917	DS	CP	C	8.5	0.0999	4.851	2.768	N/A	712
(Alsamman 1995)	M	LTN 918	DS	CP	C	11.5	0.0730	6.781	3.614	N/A	1486
(Alsamman 1995)	M	LTN 919	DS	CP	C	10.7	0.0999	6.402	2.849	N/A	1201
(Alsamman 1995)	M	LTN 89	DS	CP	C	13.0	0.9509	3.440	1.471	N/A	3692
(Alsamman 1995)	M	LTN 91	DS	CP	C	14.0	1.7662	3.621	1.895	N/A	4448
(Alsamman 1995)	M	LTN 93	DS	CP	C	6.0	0.9509	7.958	9.245	N/A	3768
(Alsamman 1995)	M	LTN 95	DS	CP	C	6.0	1.7662	11.885	14.017	N/A	3932
(Alsamman 1995)	M	LTN 404	DS	CP	C	18.3	0.3127	13.000	3.970	N/A	2144
(Alsamman 1995)	M	LTN 406	DS	CP	C	12.0	0.2832	21.427	5.881	N/A	3314

(Alsamman 1995)	M	LTN 407	DS	CP	C	12.0	0.2832	21.324	5.330	N/A	2891
(Alsamman 1995)	M	LTN 713	DS	CP	C	42.0	1.7662	17.225	8.975	N/A	14590
(Alsamman 1995)	M	LTN 859	DS	CP	C	9.0	0.7850	3.861	2.028	N/A	5115
(Alsamman 1995)	M	LTN 860	DS	CP	C	9.5	0.7850	4.418	2.169	N/A	3425
(Alsamman 1995)	M	LTN 861	DS	CP	C	9.0	0.7850	7.373	4.637	N/A	6672
(Alsamman 1995)	M	LTN 865	DS	CP	C	10.2	0.0804	20.205	2.909	N/A	801
(Alsamman 1995)	M	LTN 866	DS	CP	C	10.2	0.0804	20.086	2.997	N/A	890
(Alsamman 1995)	M	LTN 870	DS	CP	C	10.2	0.0804	12.260	2.138	N/A	1045
(Alsamman 1995)	M	LTN 872	DS	CP	C	10.0	0.1252	27.737	13.600	N/A	867
(Alsamman 1995)	M	LTN 880	DS	CP	C	8.2	0.2134	14.648	5.242	N/A	1601
(Alsamman 1995)	M	LTN 881	DS	CP	C	8.2	0.2134	15.537	5.752	N/A	1779
(Alsamman 1995)	M	LTN 885	DS	CP	C	10.2	0.1962	7.667	1.666	N/A	1557
(Alsamman 1995)	M	LTN 887	DS	CP	C	8.7	0.1451	24.803	6.031	N/A	623
(Alsamman 1995)	M	LTN 888	DS	CP	C	8.7	0.1451	24.843	6.318	N/A	845
(Alsamman 1995)	M	LTN 891	DS	CP	C	7.8	0.1252	9.283	1.911	N/A	667
(Alsamman 1995)	M	LTN 894	DS	CP	C	5.8	0.1390	17.805	5.909	N/A	1023
(Alsamman 1995)	M	LTN 895	DS	CP	C	5.8	0.1310	14.029	4.022	N/A	890
(Alsamman 1995)	M	LTN 896	DS	CP	C	6.2	0.0851	18.414	5.489	N/A	712
(Alsamman 1995)	M	LTN 897	DS	CP	C	6.3	0.0851	23.029	8.586	N/A	823
(Alsamman 1995)	M	LTN 910	DS	CP	C	13.0	0.9144	26.090	18.507	N/A	9475
(Alsamman 1995)	M	LTN 911	DS	CP	C	13.0	0.3532	21.440	17.926	N/A	4893
(Alsamman 1995)	M	LTN 912	DS	CP	C	10.2	0.3532	19.069	19.183	N/A	7117
(Alsamman 1995)	E	LTN 923	DS	CP	C	5.6	0.1291	16.687	15.978	N/A	676
(Alsamman 1995)	E	LTN 936	DS	CP	C	10.4	0.1291	7.884	10.277	N/A	1157
(Alsamman 1995)	E	LTN 941	DS	CP	C	16.8	0.4560	6.092	5.258	N/A	3781
(Alsamman 1995)	M	LTN 158	DS	CP	C	25.1	0.9247	9.275	6.703	N/A	7695
(Alsamman 1995)	M	LTN 302	DS	CP	C	7.2	0.2832	8.035	3.581	N/A	2580
(Alsamman 1995)	M	LTN 857	DS	CP	C	24.4	0.5518	22.836	6.697	N/A	12233
(Alsamman 1995)	M	LTN 862	DS	CP	C	11.5	2.5399	6.160	3.214	N/A	12677
(Alsamman 1995)	M	LTN 867	DS	CP	C	7.7	0.0804	6.898	0.859	N/A	578
(Alsamman 1995)	M	LTN 868	DS	CP	C	7.7	0.0804	6.915	0.992	N/A	543

(Alsamman 1995)	M	LTN 869	DS	CP	C	7.7	0.0804	7.002	0.952	N/A	623
(Alsamman 1995)	M	LTN 871	DS	CP	C	7.7	0.0804	6.865	1.128	N/A	538
(Alsamman 1995)	M	LTN 886	DS	CP	C	10.2	0.1962	5.881	1.171	N/A	1259
(Alsamman 1995)	M	LTN 892	DS	CP	C	7.8	0.1252	9.345	2.156	N/A	667
(Alsamman 1995)	M	LTN 893	DS	CP	C	7.8	0.1252	9.288	2.165	N/A	832
(Alsamman 1995)	E	LTN 928	DS	CP	C	6.5	0.1214	7.385	9.663	N/A	872
(Alsamman 1995)	E	LTN 935	DS	CP	C	7.0	0.1291	13.479	10.401	N/A	1334
(Alsamman 1995)	E	LTN 937	DS	CP	C	8.4	0.1291	14.813	8.562	N/A	1201
(Alsamman 1995)	M	LTN 159	DS	CP	C	27.0	0.9352	9.231	7.041	N/A	8896
(Alsamman 1995)	E	LTN 742	DS	CP	C	24.2	0.5202	7.804	7.635	N/A	5872
(Alsamman 1995)	E	LTN 925	DS	CP	C	7.9	0.1291	5.090	12.905	N/A	814

819 * M : Mechanical Cones, E : Electrical Cones, D : Driven piles, B : Bored Piles, DS : Drilled Shafts,
820 SP : Squared Piles, CP : Circular piles, OC : Octogonal Piles, T : Triangle C : Concrete, S :
821 Steel

822
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Reference	Pile No	Length (m)	Diameter (mm)	IFR _{ave}	Setup Days	(q _c) _{ave} (MPa)	Q _s (kN)
(Chow 1996)	DK CS'T89a	11.3	324	0.64	180	14.19	395
(Chow 1996)	DK CS'T89b	11.6	324	0.64	270	14.23	435
(Chow 1996)	DK CS'T94	11.6	324	0.64	1950	14.23	750
(Chow 1996)	DK CL'T89a	11.3	324	0.66	180	14.19	458
(Chow 1996)	DK CL'T89b	11.6	324	0.66	270	14.23	548
(Niazi 2014)	E1/30.5-2	30.5	762	0.86	15	8.09	2943
(Niazi 2014)	E1/38.7-3	38.7	762	0.86	15	12.63	8787
(Niazi 2014)	E1/47.0-2	47.0	762	0.86	15	16.89	13657
(Niazi 2014)	E2/46.7-2	46.7	762	0.86	15	17.85	11028
(Niazi 2014)	E2/47.0R-2	47.0	762	0.86	15	18.12	19482
(Schneider 2007)	SPP P01	4.0	89	0.56	70	5.36	50
(Schneider 2007)	SPP P01	4.0	89	0.56	376	5.36	66
(Schneider 2007)	SPP P02	4.0	42	0.48	70	5.16	26
(Schneider 2007)	SPP P02	4.0	42	0.48	376	5.16	52
(Schneider 2007)	SPP P04	4.0	89	0.55	70	5.14	61
(Schneider 2007)	SPP P04	4.0	89	0.55	376	5.14	86
(Schneider 2007)	SPP P05	4.0	114	0.59	71	5.01	69
(Schneider 2007)	SPP P05	4.0	114	0.59	374	5.01	86
(Schneider 2007)	SPP P06	4.0	89	0.56	71	5.50	57
(Schneider 2007)	SPP P06	4.0	89	0.56	374	5.50	86
(Schneider 2007)	SPP P08	2.5	42	0.48	71	2.70	12
(Schneider 2007)	SPP P08	2.5	42	0.48	259	2.70	25
(Schneider 2007)	SPP P09	2.5	34	0.45	71	2.65	6
(Schneider 2007)	SPP P09	2.5	34	0.45	259	2.65	13
(Schneider 2007)	SPP P10	3.5	34	0.45	71	3.07	9
(Schneider 2007)	SPP P10	3.5	34	0.45	259	3.07	17
(Schneider 2007)	SPP P11	2.5	89	0.56	71	2.82	22
(Schneider 2007)	SPP P11	2.5	89	0.56	259	2.82	40
(Gavin et al. 2013)	BD S5	7.0	340	0.73	220	16.32	990
(Gavin et al. 2013)	BD S2	7.0	340	0.73	2	16.32	344
(Gavin et al. 2013)	BD S3	7.0	340	0.73	13	16.32	665
(Yang et al. 2015)	HG P2B	17.6	711	0.86	43	9.78	1400
(Yang et al. 2015)	HG P2D	17.7	711	0.85	34	9.76	1400
(Yang et al. 2015)	HG P3B	17.6	711	0.86	116	9.76	1900
(Yang et al. 2015)	HG P3D	17.7	711	0.86	30	9.76	1120
(Yang et al. 2015)	HG P4B	17.7	711	0.86	37	9.76	1550
(Yang et al. 2015)	HG P4D	17.7	711	0.86	32	9.76	1250
(Yang et al. 2015)	HG P5B	17.7	711	0.86	36	9.76	1420
(Yang et al. 2015)	HG P5D	17.8	711	0.86	29	9.76	950
(Yang et al. 2015)	L1-1	21.5	508	0.80	43	4.18	980
(Yang et al. 2015)	L2-1	21.5	508	0.80	135	4.18	990
(Yang et al. 2015)	L3-1	21.5	508	0.80	218	4.18	1160
(Yang et al. 2015)	L4-1	21.5	508	0.80	365	4.18	1065

(Yang et al. 2015)	L5-1	21.5	508	0.80	730	4.18	1080
(Yang et al. 2015)	L6-1	21.5	508	0.80	730	4.18	900
(Yang et al. 2015)	L7-1	21.5	508	0.80	30	4.18	600
(Beringen et al. 1979)	1-T	7.0	356	0.74	37	22.70	820
(Beringen et al. 1979)	3-T	5.3	356	0.73	19	18.04	530
(Yang et al. 2015)	P(O)-T1	34.0	1220	0.95	4	13.68	3860
(Yang et al. 2015)	P(O)-T2	41.0	1220	0.95	4	14.14	3740
(Yang et al. 2015)	BD	38.1	660	0.84	30	16.75	5250
(Yang et al. 2015)	CL-T	11.3	324	0.72	175	13.24	444
(Yang et al. 2015)	R1-T	19.3	457	0.78	9	16.27	1450
(Yang et al. 2015)	C1-T	10.0	457	0.78	69	19.88	820
(Yang et al. 2015)	Ia-T	10.5	763	0.86	7	21.99	1660
(Yang et al. 2015)	Ib-T	18.7	763	0.86	2	34.54	8400
(Yang et al. 2015)	Ic-T	27.0	763	0.86	12	40.55	12500
(Yang et al. 2015)	II-t	26.7	763	0.86	6	42.24	9500
(Han et al. 2020)	TP	30.5	660	0.81	8	9.28	2264
(Igoe et al. 2013)	TP-110	4.0	200	0.65	82	8.17	110

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Figures

Figure 1

Interpretation of the input features from CPT results; a) (qc)end for the soil above the pile tip is weaker, b) (qc)end for the soil above the pile tip is stronger, c) (qc)ave, d) (fs)ave

Figure 2

Flowchart of the proposed approach.

Figure 3

Distribution of statistical measures among the ML methods and traditional methods in 120S_5F_9ML, (a) R^2 , (b) RE

Figure 4

Distribution of statistical parameters among the MLM and traditional methods in 120S_4F_4ML, (a) R^2 , (b) RE

Figure 5

Boxplot visualization of the 219S_4F_4ML analysis set, (a) R^2 , (b) RE

Figure 6

Boxplot visualization of the 60S_5F_9ML analysis set, (a) R^2 , (b) RE.

Figure 7

Boxplot visualization of the 49S_5F_9ML analysis set, (a) R^2 , (b) RE

Figure 8

Regression graphs of 120S_4F_4ML, (a) RF, (b) GPR, (c) RVR, (d) VHGPR, (All folds are used as testing data)

Figure 9

Regression graphs of ML methods and traditional methods

Figure 10

Regression graph of RVR method compared with traditional methods, ($R^2 = 0.91$ for RVR, 0.72 for Schmertmann, 0.74 for DeRuiter, and 0.84 for LCPC)

Figure 11

Regression graphs of 49S_5F_9ML, (a) MARS, (b) RF, (c) GPR, (d) VHGPR, (All folds are used as testing data)

Figure 12

Regression graph of VHGPR method compared with traditional methods, (R^2
= 0.96 for RVR, 0.83 for UWA, 0.78 for NGI, and 0.69 for Fugro)