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Effect of SVM Kernel Functions on Bearing Capacity Assessment of Deep Foundations

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ABSTRACT

Pile foundations are vastly utilized in construction projects where their capacities (pile bearing capacity, PBC) should be determined in different stages of construction. A highly reliable and accurate prediction model can lead to many advantages, such as reducing the construction cost, shortening the construction timeline, and providing safety construction. Hence, the aim of this study is the developments of statistical and artificial intelligence (AI) models for predicting bearing capacities of 141 piles. At the preliminary of the study, features or inputs of this study to predict PBC were selected trough simple regression analysis. Then, this study presents different kernels of support vector machine (SVM) technique, i.e., the dot, the radial basis function (RBF), the polynomial, the neural, and the ANOVA to predict the PBC. The aforementioned models were evaluated by several performance indices and their results were compared using a simple ranking system. The results showed that the SVM-RBF model is able to achieve the highest coefficient of determination, R2 values which are 0.967 and 0.993 for training and testing stages, respectively. It is important to mention that a multiple regression model was also employed to predict PBC values. The other SVM kernels were provided a high degree of accuracy for estimating PBC, however, the SVM-RBF model is recommended to be used as a powerful, highly reliable, and simple solution for PBC prediction.

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1. Introduction

Pile foundation supports the essential constituent of the superstructure by transferring the overall load from the structure to beneath the soil or earth [1–3]. Pertaining to that information, the value of pile bearing capacity (PBC), which is delineated as the total load a pile can hold to support the superstructure, holds substantial significance in the design of pile foundations, whereby casualties and loss of property as a result of pile failure can be avoided [4–6]. In the past few decades, field test such as Static Load Test (SLT) and High-Strain Dynamic Testing (HSDT) are preferred to be conducted in relevant projects to determine the factors including the bearing capacity of the pile. However, it is impossible to carry the field tests on each pile due to their limitations such as time consuming and costly [3,7–9]. Since estimation of PBC is one of the hot topics in the of area geotechnical engineering [10], different methods in estimating PBC have been proposed by many researchers. Nevertheless, the model accuracy and consistency is always of prime importance and interest in such case.

There are many parameters influencing the PBC in the real scenario which can be divided into three categories i.e., pile geometry, soil condition and field test setting [11–15]. These categories with their sub-factors are presented in Figure 1. Among all effective factors, the pile geometry group including the embedment length of pile beneath the soil, the soil type and the apparatus used in the field test are considered the most influential parameters in measuring/predicting the PBC. The whole available models in the area of PBC estimation can be categorized into 3 general groups which are i) empirical/theoretical, ii) statistical and iii) artificial intelligence (AI)/machine learning (ML). The models in the first group are developed based on the theory from previous researchers and also the laboratory test data. The calculation of PBC values using empirical/theoretical techniques e.g., the Terzaghi formula (Terzaghi 1943) and the Vesic formula [17], could not be enlightened models for developing a reliable predictive tool specially when a new data is available [18]. The reason(s) may refer to the fact that these methods are lengthy in calculation and there are many assumptions that need to be made. Other than empirical/theoretical models, statistical models were also used to perform a solution for the PBC prediction [19,20]. Typically, the statistical model is a developed mathematical equation from the relationship between the predictors (inputs which are more than one variable) and the outcome (output) variables. Although statistical models are good in terms of their simplicity and efficiency, the performance capacity of these models is low, especially when extreme values are found in the data [20]. The models also do not show robustness that can solve complex and nonlinear relationships [9].

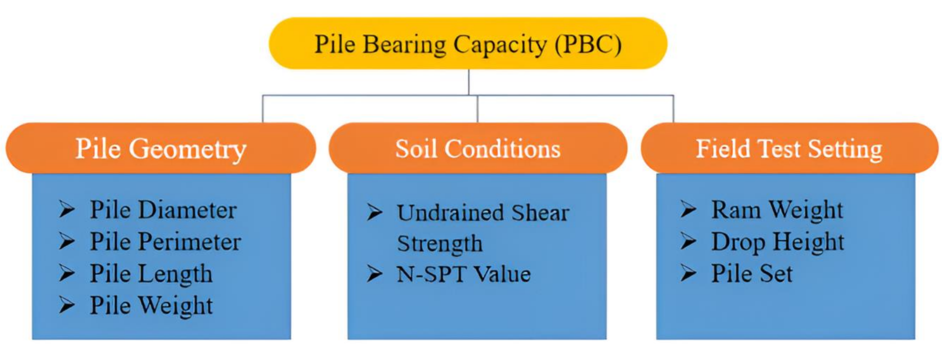

Fig. 1. The most important categories on the PBC prediction.

In this modern era, human cannot live without computer, programming, and the applications of computational-based models. With the needs and requirements from the society, technology is improving and advancing from days to days. In essence, AI/ML techniques are normally dealing with math, algorithm and a sense of creativity [14,21,22]. They have been efficiency applied in solving problems in various areas of engineering [23–29]. In the area of the PBC estimation, there are several published AI/ML works in literature. For instance, Pal and Deswal [30] and Momeni et al. [5] suggested a solution for solving PBC problem based on the Gaussian process regression (GPR) model and reported its successful application for predicting PBC values. In another study, Momeni et al. [31] conducted a study to propose a model on PBC prediction using a hybrid genetic algorithm (GA)-artificial neural network (ANN). They used a total number of 50 data samples for their study and received an excellent level of performance capacity for their proposed model. In another interesting study, Harandizadeh et al. [32] made use the applications of improved neuro-fuzzy approaches in predicting the PBC and their model received a very low system error in forecasting PBC. Chen et al. [33] have developed several hybrid AI/ML models including neuro-genetic, neuro-imperialism, genetic programming (GP), and ANN to estimate PBC values. After evaluation these techniques, the GP model was scored the highest coefficient of determination (R^2) value among all proposed models. It seems that AI/ML models are able to provide a new solution and at the same time highest level of accuracy among all three described groups in estimating PBC values.

After reviewing, different kinds of AI/ML models in the area of PBC prediction, there is only a limited number of support vector machine (SVM) studies available for predicting pile capacity [20,34]. SVM is a ML method that has demonstrated very encouraging and excellent results in the geotechnical field such as liquefaction assessment [35], tunneling and underground space technology [36], dam, embankment and retaining wall [37,38], soft soil issues [39,40], rock strength issues [41] and blasting environmental issues [42]. In addition, to being a powerful modelling technique, SVM can be used to provide the user with advice regarding the variables lack in the training set database. Furthermore, SVM usually comes with different kernel functions such as linear, polynomial, sigmoid and radial basis function (RBF) that are able to simplify the complexity of nonlinear data.

This study aims to evaluate the feasibility of SVM model with the use of different kernel functions to predict PBC values. To this end, various SVM kernels i.e., dot or linear, RBF, polynomial, neural, and ANOVA are used to solve the problem in hand. Then, these kernels are evaluated based on their performance capacities in predicting PBC values and the best SVM kernel is selected to introduce.

2. Materials and methods

2.1. SVM background

Support vector machine (SVM) utilizes various kernel functions to reform the non-linear data sets by transforming the datasets from higher dimension to a lower dimension. Then, a separating hyperplane can be created in the central of the maximum margin separating the support vectors [43]. Sometimes, support vectors which are defined as the closest training points to the hyperplane, can be more than two. Figure 2 depicts the geometric point of view of the entire input space divided by a hyperplane into 2 parts (i.e., +1 and -1). The hyperplane may appear whether in a line or surface form depending of the dimensional space of the support vectors [44]. The margin between the hyperplane and support vectors needs to be maximized by minimizing the *w* value. The margin is strongly dependent with the parameter C in SVM where C is known as a hypermeter in controlling the misclassifying training example. To identify the function is in positive or negative, the equation below can be used:

$$y = f(x) = w(\theta) + b \tag{1}$$

where inputs and output of the model are denoted as x and y, respectively, w is the weight vector of x, (θ) is the feature mapped non-linear from the input space x, and the b infers the bias of the model. Hence, $f(x) \geq 1$ will be considered as positive examples and $f(x) \leq -1$ is the negative examples.

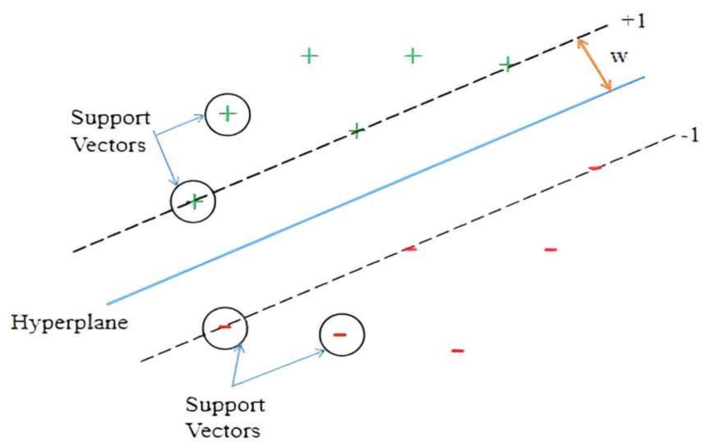

Fig. 2. Schematic of the SVM.

Kernel is a mathematical function that serves as a link bridge for non-linear function to linear one. Figure 3 displays the structure of kernel functions in transforming the data. In addition, the performance of SVM is greatly influenced by kernel functions.

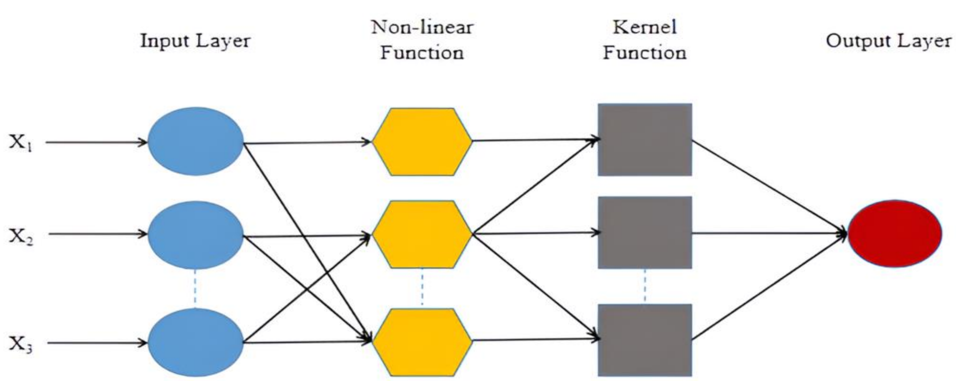

Fig. 3. Typical structure of kernels function.

Often, data sets can be classified into two different cases, which are separable and non-separable. For separable case, the hyperplane can be easier drawn and straightforward. So, linear kernel function is commonly-used in the linear separable case. This is because linear kernel function is the simplest kernel function grant by the inner product or dot between the functions. In engineering problems, non-separable data is common and always appeared. Hence, other functions can be utilized in order to produce the hyperplane with maximum margin. For instance, RBF is the most favorable kernel used in the case when the relation between two attributes are non-linear. Besides, RBF provides more trustworthy results as it has higher capability in interpolation but once the extrapolation is in huge range, RBF becomes weak and not suitable. Moreover, neural kernel or also known as sigmoid, which has similar behavior like RBF for certain parameters is commonly-used to solve for non-separable data [45]. This neural kernel in SVM is a kind of multi-layer perception without hidden layer. In addition, the RBF and neural kernel functions may be influenced by the hyper-parameter, gamma. The main function of the gamma is to decide the curvature of the hyperplane in the decision boundary. Furthermore, polynomial kernel function is another commonly-used function where it represents the feature space over polynomials of the original variable. Lastly, ANOVA kernel function is the extend version of RBF function which is able to combine the RBF and laplacian formulations. Table 1 shows the kernel formulas applied in this study. In this figure, 'd' is the polynomial degree while 'γ' is the Gamma value for RBF, neural and polynomial kernels, x_i and x_j are the vector inputs.

Table 1
Formulas for different kernel functions used in this study.

Kernel Function	Equation
Linear	$G(x_i,x_j) = \exp(-y\mathbb{D}x_i - x_j\mathbb{D}^2)$
RBF	$G(x_i,x_j) = (-yx_i^t x_j + 1)^d$
Neural	$G(x_i,x_j) = \mathrm{Tanh}\ (-yx_i^t x_j + 1)^d$
Polynomial	$G(x_i,x_j) = x_i^t x_j$
ANOVA	$G(x_i,x_j) = \exp(-y(x_i - x_j))$

2.2. Case study and collected data

The HSDT or commonly-known as pile driver analyzer (PDA) tests were conducted in Pekanbaru area, Indonesia (Figure 4). Pekanbaru city is the important city in Indonesia and it was declared as the capital of the Riau district in Sumatra Island. The population of Pekanbaru has recorded approximately 1 million in the year of 2014 with the increment of 3.5% per year from 1998. Rapid growth of economic needs infrastructure facilities and tower building to support human activities. With increasing the number of construction projects, the number of PDA tests must be also increased to check capacity of the piles used as foundations of super-structures. Therefore, in order to propose SVM models with various kernels for prediction of PBC, a number of 141 PDA tests were carried out in Pekanbaru, Indonesia. The tests were performed on the precast concrete piles. Figure 5 shows an example of PDA test using the pile driving analyzer equipment with Control and Provisioning of Wireless Access Points (CAPWAP) software to analyze the PBC. Various parameters including pile set, S, pile diameter, D, pile length, L, drop weight, H, and ram weight, W, were measured for these 141 tests. Of course, their PBC values were recorded as the ultimate objective factor of this study to be predicted. As discussed in introduction section, the collected/measured variables are all important for estimating PBC values. Therefore, the authors decided to use D, L, H, S, and W as model predictors or inputs to forecast PBC values. In order to give a better view of the used data, Table 2 lists 30 data samples comprising the input and output parameters out of the whole data (i.e., 141 samples). The ranges of (226-600 mm), (3-48 m), (12-90 kN), (0.2-3 m), and (291-3680 kN) were used for D, L, W, H, and PBC, respectively, in the modelling of this study.

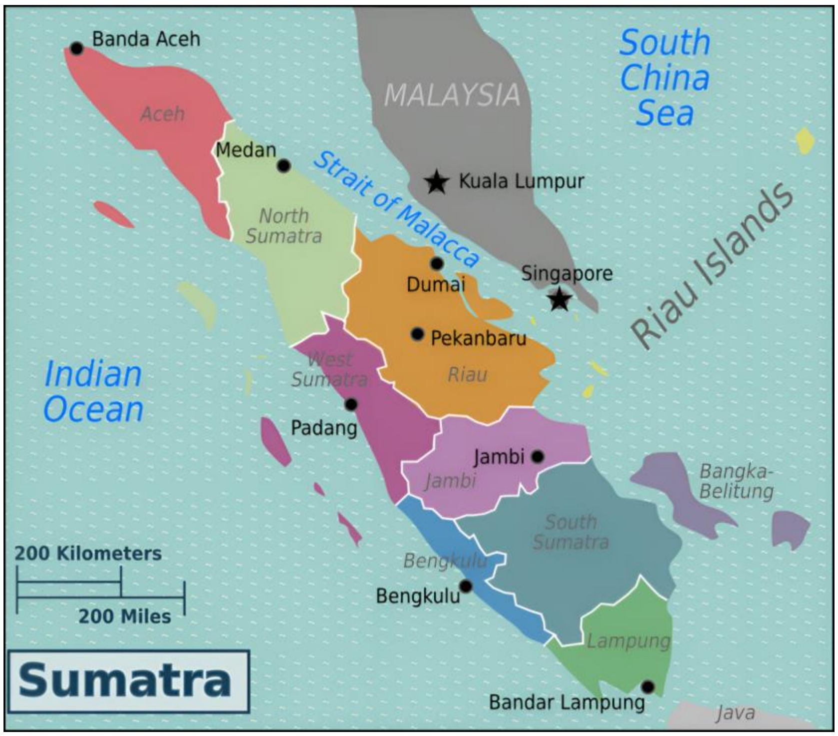

Fig. 4. Location of Pekanbaru, Indonesia.


Fig. 5. PDA test conducted in Pekanbaru, Indonesia.

Table 2
A part of input and output variables used in the modelling.

Sample No.	Inputs				Output
	Pile Diameter (mm)	Pile Length (m)	Ram Weight (kN)	Drop Height (m)	Pile Bearing Capacity (kN)
1	282	8	12	1	555
2	282	8	12	1	623
3	282	3	12	1	536
4	282	3	12	1	850
5	282	3	12	1	648
6	282	8	12	1	291
7	282	11	13	1.5	1,572
8	282	11	13	1.5	1,450
9	282	13	13	1.5	854
10	282	14	13	1.5	818
11	282	14	13	1.5	980
12	282	13	13	1.5	1,063
13	395	28	35	1	1,341
14	480	29	45	1	1,409
15	480	29	45	1	2,200
16	480	29	45	1	1,650
17	226	10	13	1	1,058
18	226	7	13	1	942
19	226	11	13	1	774
20	226	8	13	1	749
21	226	8	13	1	780
22	226	8	13	1	588
23	226	8	13	1	707
24	451	12	90	0.4	3,530
25	306	17	90	0.3	2,790
26	306	15	90	0.3	2,900
27	451	23	90	0.4	3,430
28	451	14	90	0.4	3,460
29	226	17	25	0.4	780
30	226	17	25	0.4	770

2.3. Step-by-step overview of research

The first point to begin in this paper is setting up the research goal which is to introduce an applicable AI/ML technique to forecast the PBC. In this case, SVM predictive model is considered as a high level of performance and the errors is targeted to be lesser than 10%. Then, the research continues with the reviewing of past related published studies by the experts. After reviewing plenty of papers regarding the predictive model for PBC, it was found that there is a lack of study using SVM model with different kernels in forecasting the PBC. Various kernel functions of SVM are able to simply the complex and non-linear relations between inputs and output variables. After identifying the study problem, a series of quantitative data was obtained from the PDA tests. After compiling the data, the filtration was performed using ‘outlier labeling rule' which is proposed by Hoaglin and Iglewicz [46] to check for missing data and outliers before analysis. The next step is related to input selection, which was done using simple regression analysis. The next objective of this paper is to propose SVM models with different kernels to forecast the PBC. The SVM was modelled using Rapidminer software, which is a user-friendly modelling software for researchers. Eventually, the capacity of PBC predicted by each model was tested using important performance indices and also a simple ranking system. Then, the best SVM kernel was selected and introduced as the most powerful one for prediction of the PBC. Figure 6 illustrates the research methodology procedures of this study.

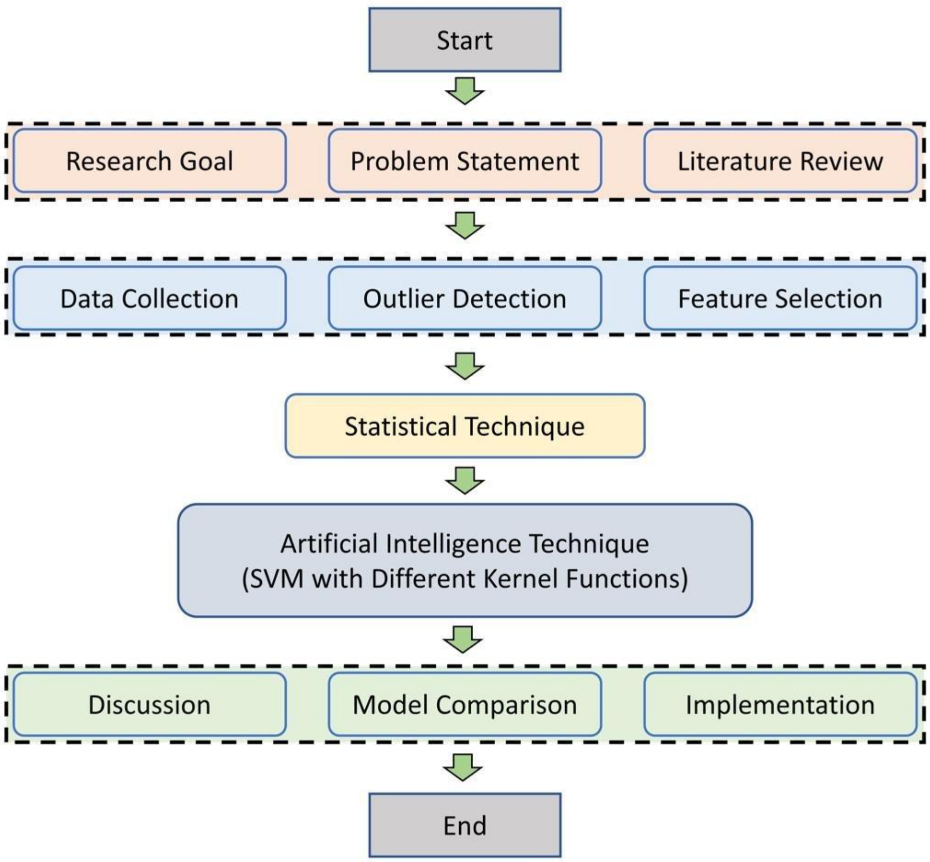

Fig. 6. Methodology procedure flowchart.

2.4. Performance index

To identify the most precise model, different performance indices must be taken into account during the modelling and evaluation parts. After reviewing previous investigations, the authors decided to apply the R^2, a20-index, root mean square error (RMSE), variance account for (VAF%), and mean absolute error (MAE) on the ML/AI results. The values of 1, 1, 0, 100% and 0 are considered as the perfect values for these indices, respectively. The formulas of these indices are presented in Table 3. In this table, n refers to total number of database, O stands for the measured database, O' indicates the predicted values of O, and $\bar{O}$ refers to mean value of O, m^{20} indicates the rate of experimental value/predicted value that lies between the range of 0.80 to 1.20. These indices can be calculated for train and test phases.

Table 3
Equations of performance indices used in this investigation.

Index	Equation
RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(O'-O)^2}$
R^2	$1-\frac{\sum_i (O-O')^2}{\sum_i (O-\bar{O})^2}$
VAF (%)	$[1-\frac{var(O-O')}{var\ (O)}] \times 100$
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert O-O'\rvert$
a20-index	$\frac{m^{20}}{n}$

3. PBC modelling

3.1. Input selection

It is important to mention that one of the shortcomings and disadvantages of ML/AI models is their limited practical application in different areas of engineering. We as engineers should always try to make them as simple as possible in practice for other researchers and designers. In this way, one of the possible options is related to the number of inputs that we need to give to the system. The level of complexity can be decreased by reducing the number of input parameters [47]. Another point is related to the fact that if a lower number of inputs are needed to collect, the process of data collection would be easier and faster compared with the situation in which we need to collect and have all inputs. Based on above discussion, the input or feature selection was conducted through simple regression analysis. To do this, different trend line functions including linear, exponential, power and logarithmic were used between predictors and the PBC and they were evaluated using R^2. The results of these analyses are presented in Table 4. As shown in this table, there are a wide range of R^2 for different predictors. It is obvious that parameters of D and W have a deep impact on PBC results. However, L and S showed the lowest influence on the system output because they received the lowest R^2 values. In this stage, in order to remove only one parameter among them, the previous investigations were again reviewed. Based on this review and considering the fact that pile geometry category has a stronger effect on PBC results compared to field test setting category, the authors decided to remove S from the predictors. Therefore, variables i.e., D, L, W and H were set as model inputs in this study to predict PBC values. In the following sub-section, SVM modeling process and steps will be described.

Table 4
Summary of simple regression analysis for selecting input parameters.

Parameter	Trend Line Function	Relationship	R^2
D	Linear	PBC = 6.6942D - 418.42	0.354
	Exponential	PBC = $395.42e^{0.004D}$	0.317
	Logarithmic	PBC = 2538.5ln(D) -12862	0.380
	Power	PBC = $0.1715D^{1.5728}$	0.357
L	Linear	PBC = -5.5717L + 1959.9	0.004
	Exponential	PBC = $1549.2e^{-1E-04L}$	5E-06
	Logarithmic	PBC = 121.42ln(L)+ 1472.9	0.005
	Power	PBC = $1015.2L^{0.1409}$	0.016
S	Linear	PBC = -24.006S + 1962.3	0.004
	Exponential	PBC = $1600.3e^{-0.007S}$	0.001
	Logarithmic	PBC = 205.02ln(S) + 1519.2	0.017
	Power	PBC = $1138.4S^{0.1985}$	0.038
W	Linear	PBC = 29.751W + 199.35	0.698
	Exponential	PBC = $560.27e^{0.0185W}$	0.658
	Logarithmic	PBC = 1105.7ln(W) - 2394.3	0.579
	Power	PBC = $104.45W^{0.7044}$	0.576
H	Linear	PBC = -529.81H + 2160.6	0.049
	Exponential	PBC = $1788.1e^{-0.238H}$	0.024
	Logarithmic	PBC = -345.5ln(H) + 1610.6	0.037
	Power	PBC = 1431.6H-0.117	0.011

3.2. SVM modelling

The ultimate aim of this study is to introduce a new solution for prediction of PBC based on SVM and its different kernels. From the previous section, it was decided to use four input parameters of (H, W, L, and D) out of the collected variables which were S, H, W, L, and D. As mentioned before, the Rapidminer as an easy and fast software, was selected to conduct modeling of SVM with various kernels for PBC estimation. In AI/ML works, there is an important stage prior to modeling which is data division for purposes of development and assessment. For the purpose of model development, a portion of 80% was randomly selected from the whole 141 data samples while for the purpose of model assessment, another remaining portion (20%) of the data samples, was allocated. These divisions were performed based on reviewing the previous studies [48–50]. In the next stage, a SVM flowchart is created in the software which is shown in Figure 7. The order started with inserting the database for model developed. Once the database is inserted into the software, filter example is necessity but not a must. This step is to filter out the outliers such as non-numerical data, symbols which are not recognize by the system. Next, identifying the input parameters, outcome variable and the predicted variable can be specified in the set role. Then, all mentioned parameters should be connected to the SVM operator. In this SVM operator, the software enables us to choose the kernel functions. Hence, in such case, 5 different kernel functions i.e., dot/linear, RBF, polynomial, neural, and ANOVA were selected in predicting the PBC values. Furthermore, the value of complexity index, *C*, the optimizer parameter, convergence epsilon and kernel degree for each kernel function need to be designed. In this study, the mentioned parameters were determined using trial-and-error with the aim of obtaining the highest performance prediction for each kernel. Table 5 presents the final values for the effective SVM parameters for each kernel. These models and their performance ability in predicting PBC values will be discussed later.

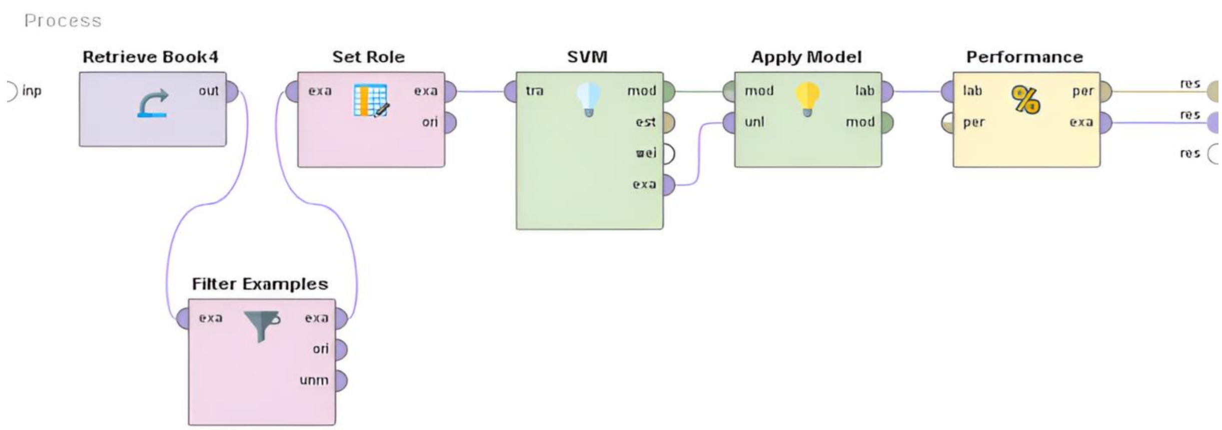

Fig. 7. Flowchart of setting up SVM in Rapidminer software for PBC prediction.

Table 5
The final values related to effecting SVM parameters for each kernel.

Kernel Type	Dot	RBF	Polynomial	Neural	ANOVA
Complexity Constant, C	1.0E-5	5.0E-6	5.0E-5	5.0E-4	5.0E-4
Convergence Epsilon	0.10	0.20	0.01	0.01	0.01
L Positive	1.30	1.00	1.50	1.50	1.50
L Negative	1.30	1.00	1.50	1.50	1.50
Kernel Degree	-	-	2.00	-	3.00
Kernel Gamma	-	2.00	-	-	4.00
Kernel Parameter A	-	-	-	0.01	-
Kernel Parameter B	-	-	-	0.01	-

4. Results and discussion

From the previous sections, it was found that using only four variable as inputs would be of more interest and applicability in practice. Therefore, the modelling was done using these four input parameters (H, W, D and L) to develop the best model in forecasting the PBC. The results has proved that the elimination of parameter, S, shows an insignificant deviation in the whole database. Different SVM kernels as predictive models were conducted to predict PBC values. Since SVM is a statistical-based technique, the authors decided to apply a linear multiple regression (LMR) model on the same training and testing portions for having a fair and logical comparison. The results of models and their abilities in predicting PBC values are presented in Tables 5 and 6 where a rating approach proposed by Zorlu et al. [51], was applied on the same. In this rating system, the better models in terms of all performance insides will get the highest rates. As shown in Tables 6 and 7, SVM with RBF kernel scored a total rating of 58 (out of 60) while this rate was obtained as 40, 29, 22, 10 and 51 for LMR, Dot, Polynomial, Neural and ANOVA, respectively. As a result, RBF received the highest position among all six models in this research for prediction of PBC values.

Table 6
The obtained results of different SVM kernels together with LMR technique.

Group	Model	Index					Rating				
		R^2	RMSE	VAF (%)	MAE	a-20	R^2	RMSE	VAF (%)	MAE	a-20
Train	LMR	0.8274	0.1198	79.14	0.0865	0.5929	4	4	3	4	5
	Dot	0.8241	0.1240	80.97	0.0901	0.5044	3	3	4	3	2
	RBF	0.9669	0.0530	96.63	0.0287	0.5309	6	6	6	6	4
	Polynomial	0.7555	0.1441	60.79	0.1081	0.5133	2	2	2	2	3
	Neural	0.6434	0.2902	1.68	0.2533	0.1681	1	1	1	1	1
	ANOVA	0.8456	0.1135	82.16	0.0815	0.6106	5	5	5	5	6
Test	LMR	0.8283	0.1136	82.50	0.0886	0.4643	4	4	4	4	4
	Dot	0.8125	0.1515	65.71	0.1194	0.2857	3	3	3	3	2
	RBF	0.9934	0.0235	99.27	0.0116	0.9286	6	6	6	6	6
	Polyno-mial	0.6974	0.1549	36.68	0.1244	0.3214	2	2	2	2	3
	Neural	0.5840	0.2615	2.57	0.2170	0.2143	1	1	1	1	1
	ANOVA	0.8654	0.1040	85.04	0.0634	0.6071	5	5	5	5	5

Table 7
Ratings and positions of developed models.

Model	Rating			Position
	Train	Test	Total	
LMR	20	20	40	3
Dot	15	14	29	4
RBF	28	30	58	1
Polynomial	11	11	22	5
Neural	5	5	10	6
ANOVA	26	25	51	2

Next, SVM with ANOVA kernel with rating of 51 is the second option in predicting PBC. Then, LMR obtained 40 points as total rating followed by the SVM with dot and polynomial kernels with their ratings of 29 and 22, respectively. Lastly, SVM with neural kernel is the least accurate model among all six developed models in forecasting the PBC as it scores only 10 points. Overall, two conclusions can be drawn from the analysed results. Firstly, the AI/ML model such as SVM with RBF kernel and SVM with ANOVA kernel have higher accuracy in terms of prediction of PBC compared to the statistical LMR model. Secondly, SVM with RBF kernel model using four input parameters has the most influential result among all. Therefore, a graph of predicted PBC using simplified SVM with RBF kernel model against the actual PBC is developed for training and testing model in the Rapidminer software, which can be shown in Figures 8 and 9. In addition, a graph of difference between actual and predicted PBC values for testing set (28 data samples) is plotted using the best developed simplifies SVM with RBF kernel (Figure 10). These figures together with the obtained results of all models confirm that the RBF kernel of SVM is the best model applied in this study with the highest accuracy level and lowest system error. This model can be used for the same problem of PBC by other designers or engineers in the future.

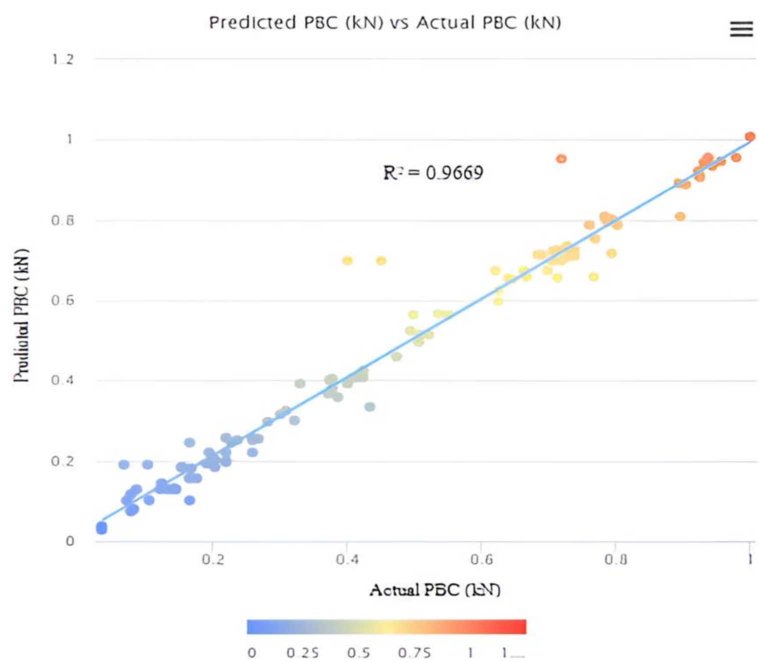

Fig. 8. Graph of predicted PBC versus actual PBC for the training set of SVM-RBF.

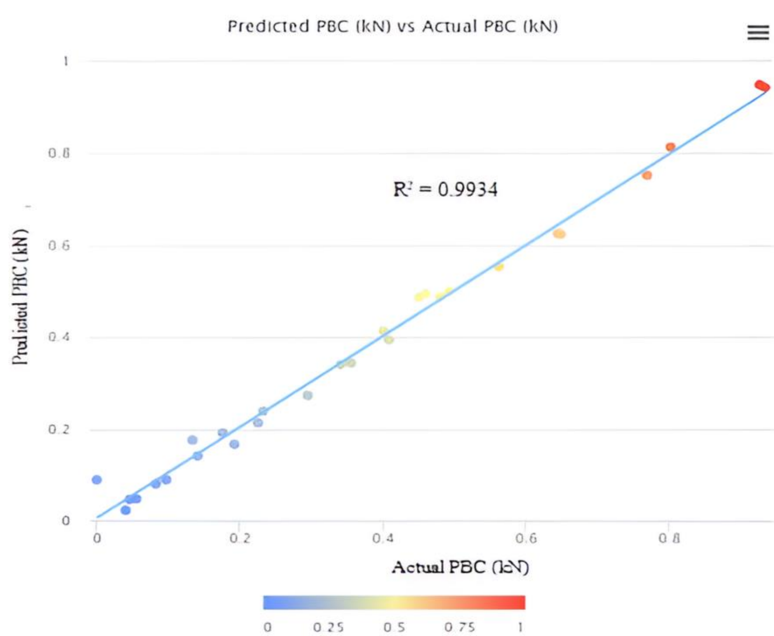

Fig. 9. Graph of predicted PBC versus actual PBC for the testing set of SVM-RBF.

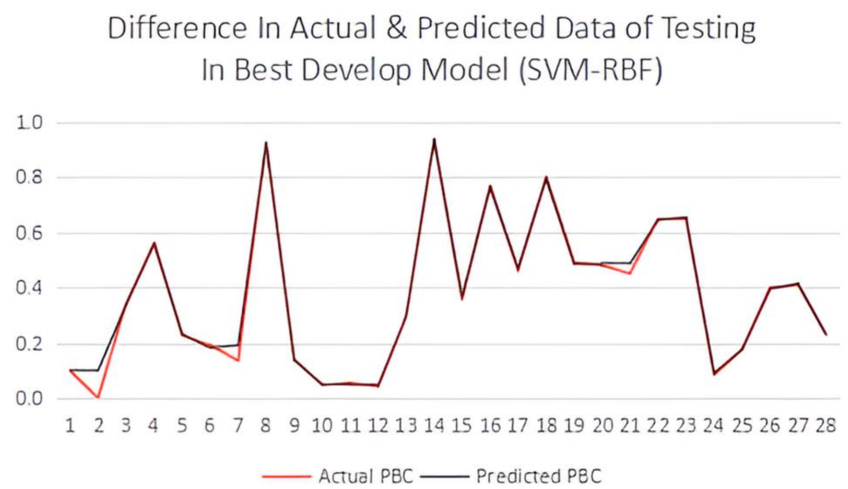

Fig. 10. Actual and predicted PBC values for 28 data samples of testing using SVM-RBF model.

Referring back to the literature reviewed, in fact, the SVM-RBF kernel developed in this study has a higher R^2 value than some of the predictive tools including the hybrid model such as ANN, general regression neural networks and combination of group method of data handling and fuzzy polynomial. Over the years, several SVM models were proposed in forecasting the PBC value. For instance, Pal and Deswal [20] investigated SVM as a potential model for prediction the static pile capacity using a database with 81 samples. They found a R^2 value of 0.967 for the RBF kernel function. On the other side, Samui and Kim [52] utilized the SVM model in forecasting the PBC value using 28 pile datasets. As a result, a training performance of R^2 = 0.951 was achieved in their model. In addition, Kordjazi et al. [53] developed a SVM model to predict PBC using 108 data set samples. The SVM model from the research aforementioned incorporated with a radial basis kernel to show a highest correlation of coefficient of 0.945. Our study has two advantages compared to the mentioned studies. First, we managed to get a higher level of accuracy compared to them which is always of interest and importance in simulation studies. Second, we used a larger data samples compared to them which allow us to propose a model with higher level of generalization. It is an important point that researchers should be aware of it and tried to develop models which can cover a larger range of data.

5. Limitations of study

One of the limitations of this study is the finite database available in the industry. In developing AI/ML techniques, the available database plays an important role. Incomplete or insufficient database is the main obstacle in developing a high performance and accurate predictive model. The reason behind this limitation is that the preparation the database is time consuming and costly. The most popular test to obtain the input is the HSDT or commonly known as PDA test. The working procedure of this test is long and required a large number of workers. In addition, heavy machinery such as excavator and mobile crane are essential for the test meanwhile the test required lots of expensive equipment and technologies.

The second limitation of this study is the proposed predictive model only applicable in the particular area or places that having the similar soil properties. The PBC may vary with the soil properties. Moreover, every single part of the world has different kinds of soil with various soil properties in term of cohesion, friction angle and so on. Although the predictive model is site specific, the algorithm and research methodology has been discovered in this study so that the prediction can be done in an easy and quick manner.

6. Conclusion

With an idea of having a ML/AI solution which is easy and simple, a series of experimental works have been done in several construction sites. The aim was to determine pile capacity together with some important factors on it. In this study, the connections between these important parameters and pile capacity were done through statistical and SVM models. First, out of all five parameters (i.e., H, W, D, S and L), S as the least effective parameter on pile capacity, was removed and the rest were used for the modeling. Then, LMR as well as SVM with five different kernels models (i.e., dot, RBF, neural, polynomial, and ANOVA) were proposed to predict PBC values. To interpreting the first-rate model among those developed models on predicting the PBC, a rating system was used. The system ranked the performance indices and the highest rate value model is known as the best model. As a result, the cumulative rate values of 40, 29, 58, 22, 10, and 51 were obtained for the LMR, SVM-dot, SVM-RBF, SVM-polynomial, SVM-neural, and SVM-ANOVA models, respectively. This shows the SVM with RBF kernel is the most successful model where the R^2 value of 0.9669 and 0.9934 was obtained for training and testing sets, respectively. The R^2 value of 0.9934 shows that SVM is one of the best developed AI models in the area of PBC prediction. Besides, the findings of AI models are better than the statistical model is proven as well since the AI model such as SVM-RBF and SVM-ANOVA obtained higher rating values than the statistical LMR model. The proposed SVM-RBF is introduced as a powerful, easy to use and simple model to be used in construction industry for predicting PBC values with a high degree of accuracy.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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