Vietnam Journal of Earth Sciences, 44(4), 470-480, https://doi.org/10.15625/2615-9783/17177

Vietnam Academy of Science and Technology
Vietnam Journal of Earth Sciences
http://www.vjs.ac.vn/index.php/jse

Estimation of load-bearing capacity of bored piles using machine learning models

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Received 29 March 2022; Received in revised form 05 May 2022; Accepted 15 May 2022

ABSTRACT

The load-bearing capacity of bored piles is an essential parameter in the foundation design of a structure. In the present study, three Machine Learning (ML) methods, namely Adaptive Neuro-Fuzzy Inference System (ANFIS), Support Vector Machine (SVM), and Artificial Neural Network (ANN), were utilized to estimate the load-bearing capacity of bored piles based on limited engineering parameters of pile and soil obtained from 75 test sites in Vietnam. These parameters include pile diameter, pile length, the tensile strength of the main longitudinal steel bar, compressive strength of concrete, average SPT index at the tip of the pile, and average SPT index at the pile body. Validation of the methods was verified using standard statistical metrics, namely Root Mean Square Error (RMSE) and Correlation coefficient (R). The results show that all the proposed models have a good potential in predicting correctly the load-bearing capacity of bored piles on training data (R>0.93) and on testing data (R>0.88). Still, the performance of the SVM model is the best (R=0.985 for training and R=0.958 for testing). Thus, the SVM model can accurately predict the load-bearing capacity of bored piles for properly designing the civil engineering structure foundation.

Keywords: Load-bearing capacity, bored pile, machine learning, ANN, ANFIS, SVM.

1. Introduction

Pile foundations are a good solution with high reliability where it is impossible to construct structures on shallow foundations. Pile foundations are designed where the soil is of low bearing capacity, stratified, or has a low strength layer at depth (De Kuiter and Beringen, 1979). Piles can also be used to transfer the load of the superstructure on the deep competent strata. There are two main types of pile foundations: bored piles and driven piles. The most common type of pile used in bridge and building constructions is a bored pile which has the advantage of easy and quick construction with equipment in all kinds of strata without damaging surrounding grounds (Burland et al., 1978). One of the most important parameters in the design of bored piles is the load-bearing capacity, which is determined using experimental or empirical

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methods (Birid, 2021). The common field experimental methods include Static Pile Load (SPL) and Pile Dynamics Analyzer (PDA). These methods are costly and thus can be conducted in limited numbers at the site (Koizumi and ITo, 1967).

Moreover, the SPL method takes a long testing time, whereas the PDA test can give large errors as waveform analysis depending on many factors (Budi et al., 2015; Momeni et al., 2014). Many studies have proposed empirical formulas for the load-bearing capacity calculation based on different soil properties and geometrical parameters of piles (Bond et al., 2013; Meyerhof, 1976; Poulos, 1989; Schmertmann, 1978). Other methods include Standard Penetration Tests (SPT), which are conducted to calculate the load-bearing capacity of piles, mainly for sandy soils (Bazaraa and Kurkur 1986; Shariatmadari et al. 2008; Shooshpasha et al. 2020; Shioi and Fukui 2021).

In general, the empirical formulas allow a quick determination of the load-bearing capacity of piles based on the dimension of the piles (diameter and length), geo-mechanical properties and types of soils, and SPT values of each soil layer (Poulos, 1989). However, these methods have drawbacks, including inappropriate parameter selection and calculation errors (Pham et al., 2020). Numerical modeling methods are also used to calculate the load-bearing capacity of piles, but these methods are susceptible to the input parameters (Ata et al., 2015; Chow and Small, 2005; Elsherbiny and El Naggar, 2013; Józefiak et al., 2015; Shooshpasha et al., 2020). Thus, numerical methods may lead to large variations in the results if parameters and models are not appropriately selected (Elsherbiny and El Naggar, 2013). Therefore, there is a great need to develop suitable load-bearing capacity prediction accurate models for designing pile foundations with limited, easily determined parameters.

Nowadays, Machine Learning (ML) methods are being utilized in many fields, including civil engineering (Le et al., 2020; Pham et al., 2021a; Van Phong et al., 2020) related to construction and foundation designs such as piles (Ghorbani et al., 2018; Momeni et al., 2014; Pham et al., 2018; Shahin, 2010). In the foundation design of the piles, most ML methods mainly focus on the prediction of the bearing strength of driven piles (Chen et al., 2020; Ghorbani et al., 2018; Kardani et al., 2020; Lee and Lee, 1996; Moayedi and Hayati, 2019; Momeni et al., 2014, 2013; Pham et al., 2020; Shahin, 2010; Zhang et al., 2021) and very few on bored piles (Al-Atroush et al., 2021; Alkroosh et al., 2015). Furthermore, these studies used Cone Penetration Test (CPT) experimental data for bearing prediction of bored piles. However, the SPT is widely used worldwide to test for bored piles load-bearing capacity prediction (Albusoda et al., 2021; Putra, 2021; Seo et al., 2021). In the present study, we have attempted to develop ML methods that can accurately estimate the load-bearing capacity of bored pile foundations. We have used three existing well-known models, namely Support Vector Machine (SVM), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Artificial Neural Network (ANN), to estimate the pile load-bearing capacity based on SPL test results as output and soil properties, SPT values, dimensions of piles as input parameters. To the author's knowledge, this is the first study to develop ML models based on SPL and SPT results to estimate the load-bearing capacity of bored piles. Therefore, this will be a new contribution or an approach for estimating the load-bearing capacity of bored piles efficiently, accurately, and economically.

The models were validated using standard statistical indexes: Root Mean Square Error (RMSE) and Correlation coefficient (R) to select the best model to be used for designing the bore file foundation. The software used in the model development is Matlab version 2014a.

2. Materials and Methods

2.1. Data used

Literature survey indicated that physical and geo-mechanical properties of soil, including SPT values and also dimensions of piles, are essential factors that have a significant influence on the load-bearing capacity of bored piles (Birid, 2021; Briaud and Tucker, 1988; Meyerhof, 1976; Ng et al., 2021; Nogueira et al., 2022; Poulos, 1989; Shooshpasha et al., 2020). In the present model's study, we have used six input parameters: pile length (L), pile diameter (D), the tensile strength of the main longitudinal steel bar (fs), compressive strength of concrete (Mb), average SPT index at the tip of the pile (N_tip), average SPT index at the pile body (N_shaft) for the prediction of the load-bearing capacity of the piles (Q_test). The data used to construct a model for estimating bored pile load-bearing capacity was obtained from 75 test sites in Vietnam. Q_test data was obtained from the tested SPL experiments.

To minimize bias during model simulation, the parameter values of the data set were normalized in the range [0, 1]. The correlation coefficient (r) of input and output variables was determined through a 7×7 symmetric matrix; as shown in Fig. 1, the value of the r of the variables varies from -1 to 1. Negative r values show a negative correlation, and positive r values show a positive correlation. The analysis of correlation properties of input parameters is indicated in Fig. 2.

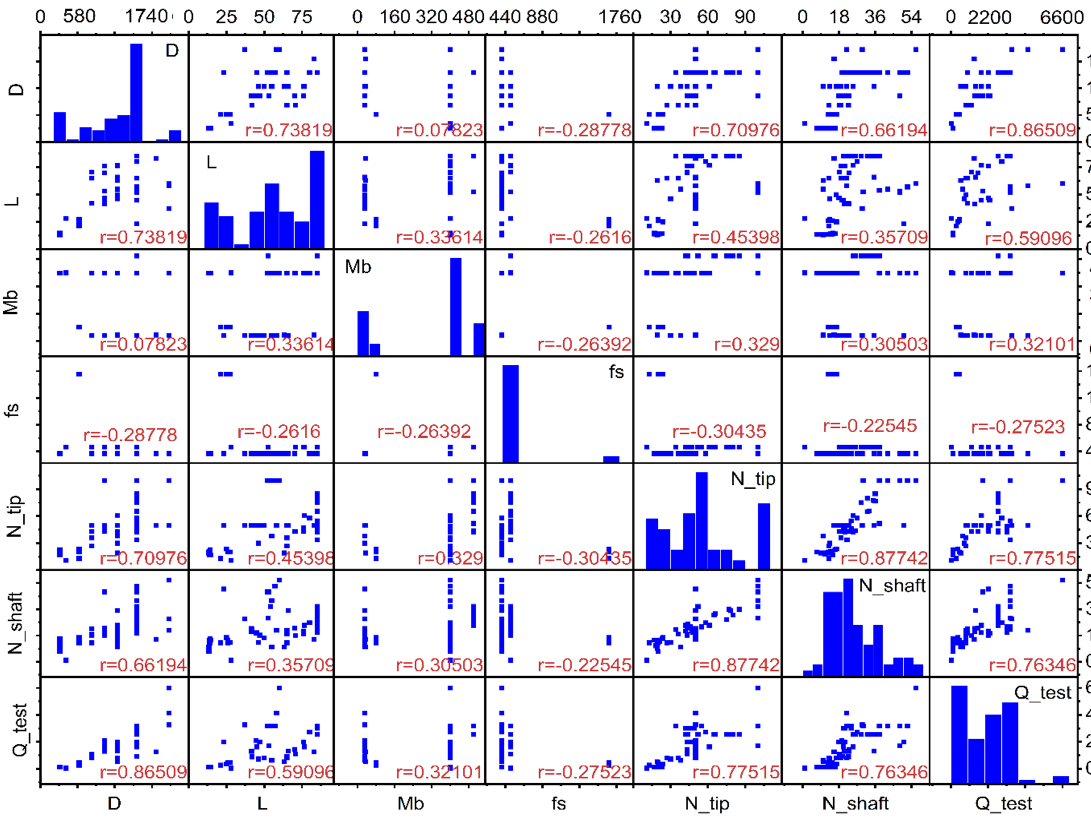

Figure 1. Correlation matrix analysis among variables

Table 1. Initial analysis of the input and output variables

Variables	Abbreviation	Unit	Min	Max	Average	median	StD
Inputs							
	D	mm	300	2000	1169.333	1500	483.784
	L	m	13.2	85	55.873	57	24.849
	Mb	Mpa	30	500	307.347	400	182.142
	fs	Mpa	400	1670	512.667	400	314.567
	N_tip		11.00	100.00	53.04	50	27.58
	N_shaft		1.00	56.00	25.17	21.80	12.578
Output							
	Q_test	ton	45	6600	2089.827	2200	1476.621

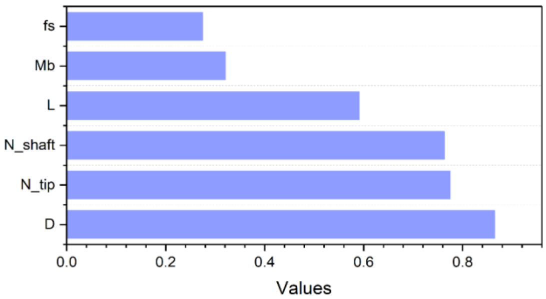

Figure 2. Correlation attribute evaluation of input variables with output variable

2.2. Methods used

The main steps of the methodology include (1) Data preparation: field test results of 75 SPL, experimental results of piles, and soil engineering properties. The data set was randomly split into two parts: testing (30%) and training (70%), (2) Model construction: the training dataset was utilized to construct the ML models: SVM, ANFIS, and ANN, (3) Model validation: the testing part data was used to evaluate the proposed models. Statistical metrics: R and RMSE were utilized to validate the models' performance to select the best model for accurately estimating the load-bearing capacity of bored piles (Fig. 3).

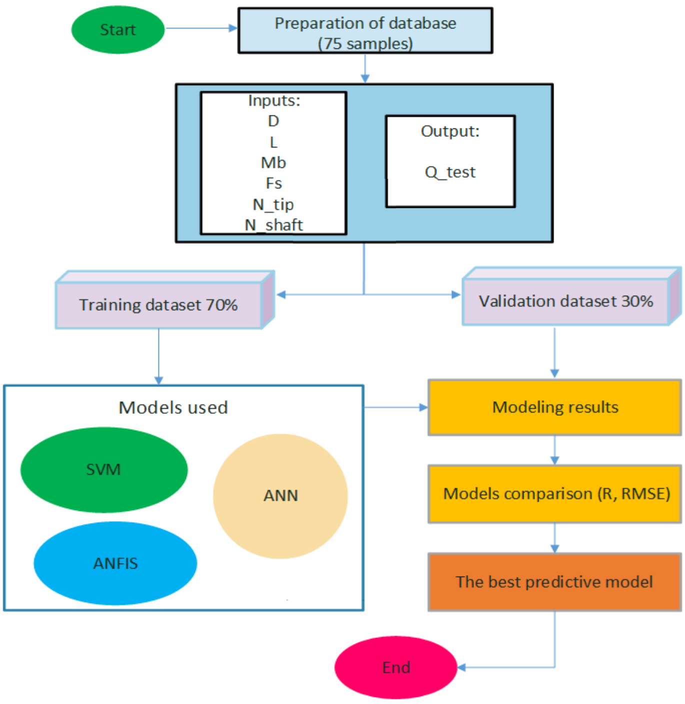

Figure 3. Methodological flowchart of the models development and evaluation processes

2.2.1. Support Vector Machines (SVM)

SVM proposed by Vapnik is an effective and common model for classification and regression problems with large dimensional datasets (Chauhan et al., 2019). SVM finds the optimal hyperplane to separate classes traversing all data elements with minimum standard deviation (e.). It uses kernel functions to solve many classification and nonlinear regression problems (Hipni et al., 2013). The basic theory of SVM can be summarized as follows:

Given a training dataset $\{(x_1,y_1),\ldots,(x_i,y_i)\} \subset X\times R$ where X defines the input data domain. The goal of e-Support Vector Regression is to find a decision function that is as flat as possible, and at the same time, the deviation on the y_i of the whole training dataset is not greater than e. For nonlinear regression, the decision function is defined as:

$$f(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(x_i, x) + b \tag{1}$$

where b is the constant that determines the balance of error margin between the flatness of and the amount of deviation ε that is accepted, α_i, α^*i are defined as the Lagrange multipliers; and $K(x_i,x)$ is defined as a kernel function as follows:

$$K(x_i, x_j) = \langle \Phi(x_j), \Phi(x_j) \rangle \tag{2}$$

where φ is the attribute mapping for kernel K.

2.3.2. Artificial Neural Networks (ANN)

ANN is one of the most common models in the family of ML algorithms. This model was first introduced by McCulloch and Pitts (Lee and Lee, 1996). ANN is a human brain-based biological simulation technique consisting of many artificial neurons connected in a network for processing information. It is a very effective technique for solving complex problems that are sometimes impossible to be solved by traditional models (Pham et al., 2018). Thus, in recent decades, ANN has been commonly used in various fields.

In ANN model, a network of nodes is linked together by weights. An ANN consists of at least 3 layers: the output layer, the hidden layer, and the input layer (Fig. 4). Such a neural network structure allows data to transfer from the input layer to the output layer in a single direction through the hidden layer/layers. The size function is usually nonlinear, enabling the predictive ability of the model's nonlinear relationships (Pham et al., 2018).

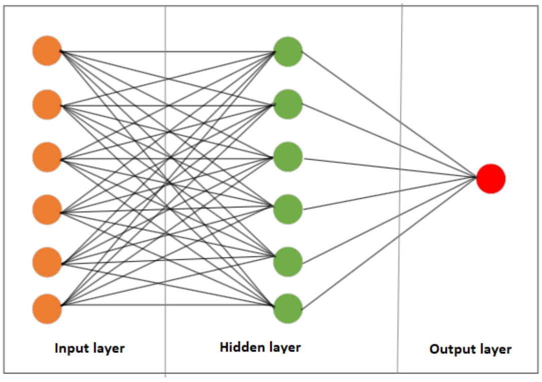

Figure 4. Typical ANN architecture

The process of training the ANN network is to find a parameter vector where the loss function has the smallest value, that is, the output error of the ANN, and the objective function is the smallest. The loss function is a nonlinear function of many parameters. The training algorithm stops when a specific condition or criterion is satisfied (Abiodun et al., 2018).

2.3.3. Adaptive Network-based Fuzzy Inference System (ANFIS)

First introduced in 1990 by Jang, ANFIS is an intelligent artificial prediction system that utilizes a hybridization of ML techniques of fuzzy logic systems and ANN networks (Van Dao et al., 2022). The proposed ANFIS can construct a fuzzy set of "if-then" rules with suitable membership functions to generate pointed input-output pairs using the associative learning process. In the succinct form, fuzzy "if-then" rules are usually utilized to capture imprecise modes of reasoning, which play an essential role in human decision-making under uncertainty and inaccurate cases (Pham et al., 2021b). The ANFIS structure (Fig. 5) includes the following main 5 classes (Ly et al., 2019): (1) Fuzzy class: This class includes membership functions determined from input parameters. The output is the value of the attribute function computed based on a Gaussian function. (2) Rule layer: Rule nodes are included in this layer, and each output from rule nodes is a product of input signals. (3) Normalized class: This class has normalized membership functions. Each node is a fixed node, and the number of nodes is equal to those in layer 2. (4) Layer of defuzzification: it implements the resulting part of the fuzzy rules, each node is an adaptive node, and the number of nodes is equal to those in layer 3. (5) Output layer: it is the sum of the outputs of all adaptive nodes in the 4th layer.

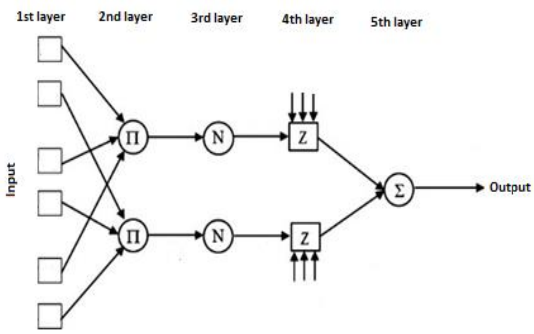

Figure 5. Typical ANFIS structure

2.3.5. Validation indicators

The statistical indicators used in this study include Root Mean Square Error (RMSE) and correlation coefficient (R) to evaluate the accuracy of the used models in estimating the bored pile load-bearing capacity. These are the two most popular indexes to measure errors in ML problems. The R-value is utilized to evaluate the correlation between the predicted and actual results, whose values are in the range of [-1;1]. The RMSE measures the average error between the actual expected and actual outputs. Quantitatively, the closer the absolute value of R is to 1, the closer the RMSE is to 0, and the better the model's accuracy. The equations determined by RMSE and R are available in published literature (Barnston, 1992; Ly et al., 2019; Pham et al., 2018; 2020; Van Dao et al., 2022).

3. Results and discussion

The performance of three studied ML models was evaluated to select the best predictive model to predict accurately bored pile bearing capacity. Comparative performance results of ANN, ANFIS, and SVM models on training and testing datasets are shown in Fig. 6a and Fig. 6b, respectively. The horizontal axis represents the number of samples in the datasets, and the vertical axis represents the load-bearing capacity of the bored pile. Experimental values are represented by black lines and predicted values obtained from these models are shown in blue for the training dataset and red lines for the testing dataset. The results show that the expected load-bearing capacity of 50 training dataset samples is relatively consistent with the model's prediction results. Similarly, with the testing dataset, 25 experimental results are good with minor errors. It shows that the estimated values of the load-bearing capacity of piles obtained from the proposed SVM model for both datasets are close to the actual results.

Fig 7 shows the performance evaluation results of SVM, ANN, and ANFIS models to estimate the load-bearing capacity of bored piles through R-value for both the testing and training phases. For the training phase, all three models have a good performance ($R>0.934$), and the SVM model shows the best performance (R=0.985), followed by the ANFIS model (R=0.98) and ANN (R=0.934), respectively. Similarly, on the testing data set, the SVM shows the best performance (R=0.958), followed by ANN (R=0.948) and ANFIS (R=0.88) models, respectively.

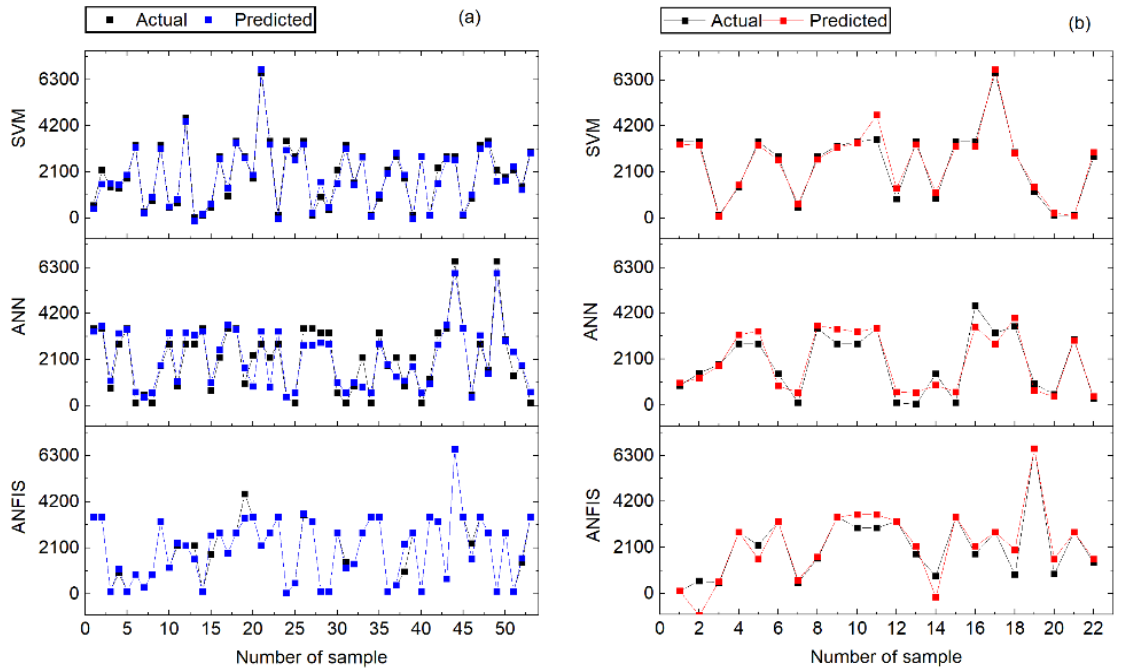

Figure 6. Predicted and actual values of bored pile load-bearing capacity with (a) training and (b) testing data

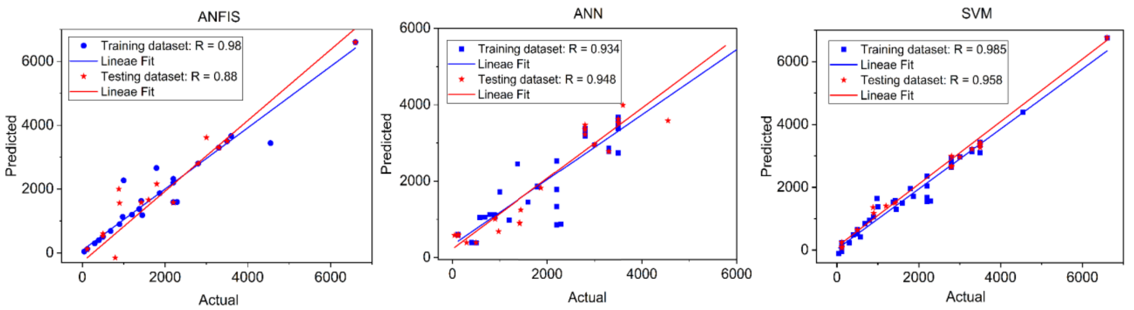

Figure 7. R values of the models

Results of the predictive model's evaluation based on RMSE value for the training and testing datasets are shown in Figs. 8a, b, respectively, and in Table 2. The vertical axis represents the RMSE value. The horizontal axis represents the number of data samples. We can see that the RMSE value of SVM is the lowest, and the RMSE curve of SVM is relatively stable compared with those of ANN and ANFIS models (Table 2).

Table 2 Analysis of error metrics of studied models

Statistical metrics	Training			Testing		
	ANFIS	ANN	SVM	ANFIS	ANN	SVM
RMSE (ton)	294.577	536.96	246.205	871.372	444.545	483.177
Error mean	0.008	1.715	51.63	48.018	-92.662	-97.309
Error StD	890.523	444.552	243.035	48.018	-92.602	-97.3

Comparison of model results indicated that the SVM is the best model in the prediction of the load-bearing capacity of bored piles compared with other models (ANN and ANFIS), which is also in line with published literature as SVM is a powerful effective ML tool in forecasting problems (Chauhan et al., 2019; Shin et al., 2005; Wang et al., 2008; Zhao et al., 2006). The SVM algorithm performs well for large data samples and often gives better results than other classes of supervised learning algorithms, especially in binary classification problems (Chauhan et al., 2019). The ANN and ANFIS models are also powerful tools for solving real-world problems (Armaghani and Asteris, 2021; Noori et al., 2010), but these two models are quite sensitive to overfitting data (Ghasemian et al., 2019). However, this problem can be handled using a combination of several optimization algorithms (Chen et al., 2020; Seifi et al., 2020). In future studies, ANN and ANFIS models may also be used to assess the prediction accuracy of bored pile load-bearing capacity along with SVM and other ML models.

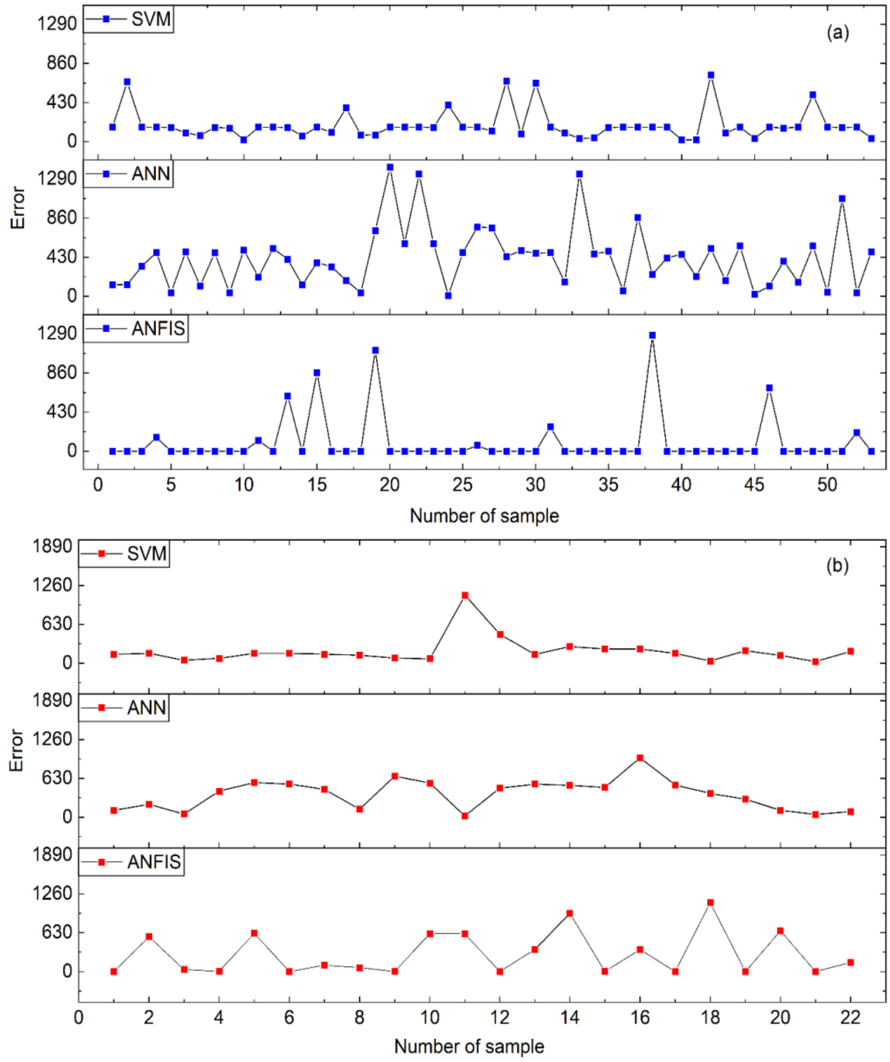

Figure 8. Values of RMSE of the studied models with (a) training dataset and (b) testing dataset

4. Conclusions

In this study, the load-bearing capacity of the bore pile was predicted using three ML models, namely SVM, ANN, and ANFIS, based on the six parameters, including pile structure dimensions and engineering properties of soil; and concrete pile. The models were validated using various statistical indicators, namely R and RMSE. Results of this study showed that all three proposed models: ANN, ANFIS, and SVM, are good in estimating the load-bearing capacity of bored piles, but the performance of the SVM model is the best (R=0.985 and RMSE=294.57). Thus, the SVM model can be used to predict the load-bearing capacity of bored piles used in the design of the foundation of the bored piles, even on different soil types. Other models (ANFIS and ANN) can also be utilized for predicting load-bearing capacity piles by solving overfitting problems using optimization techniques. In the future, it is proposed to develop new hybrid ML models to enhance the prediction performance of the studied and other models.

Acknowledgments

This work is financially supported by the Ministry of Transport (Vietnam), project title "Prediction of the load-bearing capacity of bored piles used for construction using artificial intelligence techniques and optimization" under grant number DT214012.

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