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Estimation of total bearing capacity of Pretensioned Spun Concrete Piles using a hybrid machine learning model

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ABSTRACT

In this paper, the main objective is to predict total bearing capacity (TBC) of pretensioned spun concrete piles (PSCP) using Machine Learning (ML) methods namely Reduced Error Pruning Tree (REPT), Gaussian Process (GP), Artificial Neural Networks (ANN) and two novel hybrid models including: Cascade Generalization based Gaussian Processes (CG-GP) and Cascade Generalization based Artificial Neural Networks (CG-ANN) based on data from 95 PSCP piles installed at the Hoa Binh 5 wind power plant project in Vietnam. For model development, field-estimated TBC values obtained from Pile Driving Analyzer (PDA) tests were used as the output parameter. The predictive capability of the models was validated using common statistical indicators, namely Mean Absolute Error (MAE), Coefficient of Determination (R^2) and Root Mean Square Error (RMSE) with 70% of the data used for training and 30% for testing. The results indicated that the proposed hybrid CG-ANN model (R^2 = 0.935, RMSE = 44.691 ton, MAE = 30.215 ton) outperformed all other models including CG-GP (R^2 = 0.929, RMSE = 50.738 ton, MAE = 37.812 ton), Artificial Neural Networks - ANN (R^2 = 0.926, RMSE = 47.963 ton, MAE = 32.167 ton), REPT (R^2 = 0.776, RMSE = 75.350 ton, MAE = 53.115 ton) and GP (R^2 = 0.916, RMSE = 52.785 ton, MAE = 39.967 ton) in the correct prediction of the TBC of PSCP. The results demonstrate that the hybrid CG-ANN model can serve as an efficient and reliable tool for rapid, accurate estimation of PSCP bearing capacity, thereby helping reduce the time and cost associated with elaborate field testing.

Keywords: Pile driving analyzer, Pretensioned Spun Concrete Piles, bearing capacity, hybrid model, cascade generalization, Gaussian processes.

1. Introduction

In civil engineering, Pretensioned Spun Concrete Piles (PSCP) foundations are commonly used for the construction of piled embankments, marine structures, buildings, and bridges. They have been widely adopted in soft soil foundations due to their high axial load-carrying capacity, efficient on-site construction, reasonable quality control, and cost-effectiveness (Ren et al., 2023). To evaluate the quality of the PSCP, the total bearing capacity of the piles is often used as a metric. This important parameter can be determined by various field tests, namely Pile Driving Analyzer (PDA) tests, high-strain

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dynamic testing, static axial compressive load testing, and Osterberg testing. Among these, the PDA offers faster test time and lower cost than static axial compressive load testing and is especially effective for driven piles, pressed piles, and piles lying in the middle of seas and rivers. In fact, conducting field tests requires a large area and substantial auxiliary equipment, especially for piles located in rivers and the sea. Moreover, a large amount of test data is needed to reduce experimental errors and ensure accurate calculation of the total bearing capacity of the piles. In view of this problem, many prediction models have been proposed to establish the relationship between influencing factors (such as pile type, pile construction method, pile fabrication material, pile size, length of pile submerged in soil, physico-mechanical characteristics of soil, and settlement of piles) with the pile bearing capacity (Fatehnia et al., 2018). However, in many cases, the predictions from these models differ widely from the experimental data due to significant variation in soil mechanical parameters. In addition, empirical equation-based traditional prediction models consider only a limited number of factors. Therefore, it does not reflect the complex nature of the prediction problem of the total bearing capacity of the piles.

In recent decades, several Artificial Intelligence (AI) or Machine Learning (ML)-based predictive models have been developed and applied to solve engineering problems (Anitescu et al., 2019; Guo et al., 2022a, 2022b; Guo et al., 2019; Zhuang et al., 2021). Basically, ML models are computational algorithms that learn from data and make predictions or decisions without being explicitly programmed; thus, they can effectively handle large datasets and complex problems with many input variables. In the literature, ML models have been effectively applied to predict the load capacity of various types of piles. For instance, Tarawneh (2013) compared Artificial Neural Network (ANN) and Gaussian Process (GP) for the estimation of the driven pile bearing capacity based on input variables such as drained pile-soil interface friction angle, soil friction angle, drained cohesion of the soil, flap number, pile embedded length, effective soil specific weight, and pile cross-section area. Alkroosh et al. (2015) applied the Least Squares Support Vector Machine to predict the load-bearing capacity of bore piles using several input variables, including pile diameter, average cone point resistance within the tip zone, pile length, and average cone point resistance along pile shaft. In addition, the ANN is very effectively employed in predicting the load capacity of many different types of piles (Alkroosh et al., 2015; Harandizadeh et al., 2021).

In recent years, hybrid/ensemble ML models have been known to be more advanced and effective than single ML models for prediction. Harandizadeh et al. (2021) developed and applied different ensemble models, namely ANFIS-GMDH-PSO: a combination of Group Method of Data Handling (GMDH), Particle Swarm Optimization (PSO) algorithm, and Adaptive Neuro-Fuzzy Inference System (ANFIS) methods, GMDH-based Fuzzy Polynomial Neural Network (FPNN-GMDH), and compared with a single ANN model for the estimation of the load-bearing capacity of different types of piles, including bored piles, concrete, and steel driven piles. Yong et al. (2021) developed several hybrid ML models, namely SA-GP, a combination of simulated annealing (SA) and genetic programming (GP), for predicting the ultimate bearing capacity of driven piles. They concluded that the novel model SA-GP outperformed two other single ML models, namely the adaptive neuro-fuzzy inference system (ANFIS) and

GP. Momeni et al. (2014) combined an ANN with a genetic algorithm (GA) to predict the total bearing capacity of precast concrete piles. They concluded that the novel GA-ANN model performed well and was superior to a conventional ANN. Armaghani et al. (2017) developed a novel hybrid model, namely PSO-ANN, which was a combination of ANN and particle swarm optimisation (PSO) for prediction of the ultimate bearing capacity of rock-socketed piles, and stated that the PSO-ANN improved the performance of conventional ANN model for prediction of the ultimate bearing capacity of rock-socketed piles.

In this study, two novel hybrid machine learning models, Cascade Generalization-based Gaussian Process (CG-GP) and Cascade Generalization-based Artificial Neural Network (CG-ANN), are developed to predict the total bearing capacity (TBC) of pretensioned spun concrete piles (PSCP). These models integrate cascade generalization (CG) with GP and ANN, respectively, to exploit hierarchical learning and improve prediction performance. The models are developed using input parameters derived from 95 field PDA tests conducted at different sites in Vietnam. In addition, two single ML models, namely the Reduced Error Pruning Tree (REPT), GP, and ANN, are employed as benchmark models for comparison and validation. The key novelty of this study lies in the first-time application of the CG-GP and CG-ANN hybrid frameworks for predicting the total bearing capacity of PSCPs, which has not been previously reported in the literature. Model performance is evaluated using standard statistical indicators, including RMSE, R^2, and MAE, and analyses are conducted using the Weka and Python software platforms.

2. Materials and Methods

2.1. Data used

In this work, data were collected from 95 field PDA tests conducted at the Hoa Binh 5 wind power plant project in Vietnam. This project is built on 27.7 hectares and includes 26 wind turbine towers with a capacity of 3.0−3.3 MW. The turbines are about 140 m tall. Using the PDA tests, the TBC of the piles was determined by following the equations:

$$TBC = SF + EB \tag{1}$$

Where TBC: total bearing capacity of the prestressed reinforced concrete porous piles, SF: shaft resistance, and EB: toe resistance.

In ML model studies, selecting appropriate input parameters is crucial for accurate prediction. In the present study, 12 input variables were chosen to indicate TBC as the output (Y). The 12 input parameters include: Pile diameter (X1), Embedded length (X2), Settlement of piles (X3), Modulus of dynamic elasticity (X4), Cross-sectional area at the pile top (X5), Cross-sectional area at the pile tip (X6), Mean SPT along the pile shaft (X7), Mean SPT along the pile tip (X8), cohesion along the pile shaft (X9), Friction angle along the pile shaft (X10), cohesion along the pile tip (X11), and Friction angle along the pile tip (X12). Choosing the input parameters in the models' study is based on the experience and published literature on the theoretical basis of the PDA test (Gravare, 1980; Likins et al., 1988); empirical and analytical methods (Meyerhof, 1976); and Artificial Intelligence models (Fatehnia et al., 2018). Table 1 shows the initial analysis of the variables used in this study. In the modeling, the data were randomly divided into two parts: a training dataset (70%) and a testing dataset (30%), which were used for training and validating all models.

Table 1. Analysis of value distribution of the inputs and outputs used in the modeling

No	Variables	Unit	Min	Max	Average	Standard Deviation
1	X1	mm	500.00	800.00	694.737	143.192
2	X2	m	24.00	59.00	39.001	11.619
3	X3	mm	11.838	51.182	24.306	6.435
4	X4	ton/cm^2	497.300	539.900	525.041	14.920
5	X5	cm^2	1,055.575	2,902.800	2,099.371	775.553
6	X6	cm^2	1,963.495	5,026.548	3,950.139	1,462.042
7	X7	-	5.000	14.939	11.587	2.375
8	X8	-	9.000	39.000	19.971	5.925
9	X9	kPa	7.510	44.931	20.400	11.177
10	X10	degree	0.000	12.000	7.211	3.692
11	X11	kPa	0.000	203.750	48.795	49.295
12	X12	degree	0.000	27.500	8.974	9.214
13	Y	ton	162.000	896.000	446.029	191.535

2.3. Methods used

2.3.1. REPT: Reduced Error Pruning Tree

REPT is a combination of two techniques: Decision Tree (DT) and Reduced-Error Pruning (REP). It is a fast learning process that uses tree splitting and pruning (Quinlan, 1987). In this technique, the DT is first used to simplify and reduce the complexity of the model's training process when using extensive input data. Thereafter, the REP is used to reduce the error arising from model variance (Chen et al., 2019). In addition, it uses information gain (IG) as the splitting criterion and prunes using REP (with back-fitting) (Daud et al., 2009; Jayanthi et al., 2013; Omran et al., 2016; Zhao et al., 2008). The Kullback-Leibler divergence of a conditional probability distribution can often be regarded as equivalent to the IG's expectation value (García et al., 2002). REPT is a popular ML method because it seeks a good sub-tree via post-pruning (Mohamed et al., 2012). In the present study, the REPT was selected to estimate the TBC of PSCP.

2.3.2. GP: Gaussian Processes

GP is known as a state-of-the-art probabilistic regression technique based on a Bayesian nonparametric framework (Williams et al., 2006). In this context, the Bayesian framework is widely used to provide a probabilistic perspective on the problem, and its hyperparameters determine the characteristic length scales of the GP (Neal, 1996). Basically, a Bayesian neural network with the limitation of an infinite number of hidden units is considered as a GP (MacKay et al., 2003). GP is shown as a promising technique for solving many statistical problems in the physical sciences (Ambikasaran et al., 2015). It is one of the best techniques as the problems require the flexibility of continuous functions. Nevertheless, its applications are limited by the computational cost of determinant calculation and matrix inversion (Ambikasaran et al., 2015). In this study, the GP was used as a base predictor within an ensemble framework, with the Cascade Generalization optimizer, to predict the TBC of PSCP.

2.3.3. ANN: Artificial Neural Networks

ANNs are often referred to as neural networks inspired by the structure and functioning of biological neural networks in the human brain (Krogh, 2008; Thai et al., 2022). It has gained significant popularity and has become a fundamental concept in the field of ML. It receives one or more inputs, applies a weighted sum of them, passes the sum through an activation function, and produces an output. An activation function introduces nonlinearity into the network, enabling it to model complex relationships between inputs and outputs. In ANN, neurons are organized into layers within a neural network (Hopfield et al., 1988). The three main types of layers are the input layer, hidden layers, and output layer. The input layer receives the initial input data, and the output layer produces the final output or prediction. The hidden layers, situated between the input and output layers, use activation functions and perform intermediate computations. The connections between neurons in different layers are represented by weights (Mitchell, 1997). These weights determine the strength of influence each neuron exerts on neurons in subsequent layers. During training, the weights are adjusted based on observed input-output patterns, allowing the network to learn and improve its performance over time.

2.3.4. CG: Cascade Generalization

Cascade Generalization (CG) is an effective ensemble technique that sequentially combines algorithms to improve weak predictors (Gama et al., 2000b). At a high level, the training dataset used to train a predictor is enhanced by incorporating new input features derived from the outputs of a weak predictor (Kraipeerapun et al., 2019). Out of these, tight coupling is considered more flexible than loose coupling (Zhao et al., 2004). The degree to which other prediction techniques are combined with decision tree predictors is limited by CG via the maximum cascading depth (Zhao et al., 2004). It can reduce bias and increase the complexity fitness (or flexibility) of the predictors learned by decision tree inducers. In this work, CG was used to optimize the performance of the predictors, namely GP and ANN, on which the hybrid models, namely CG-GP and CG-ANN, were generated for the prediction of TBC in PSCP.

2.3.5. Validation methods

The predictive performance of the applied models was evaluated using analytical standard parameters (Van Le et al., 2023): coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). R^2 is a commonly used regression parameter to assess model fit (Le et al., 2022; Montgomery et al., 2021). R^2 is the square of the coefficient of correlation (R) between the predicted and actual results, ranging from 0 to 1. A higher R^2 value indicates a stronger correlation between the predicted and actual values (Duc et al., 2025; Pham et al., 2021). RMSE is calculated by taking the square root of the average of the squared differences between predicted and actual outputs, while MAE is determined by computing the average of the differences between predicted and actual outputs (Nguyen et al., 2023; Nguyen et al., 2022; Rehamnia et al., 2023). Predictive performance is perfect when $R^2 = 1$, MAE = 0, and RMSE = 0. The R^2, MAE, and RMSE values are provided in the documents, and lower MAE and RMSE indicate better predictive capability of the models (Christie et al., 2021; Vu et al., 2021a; Vu et al., 2021b).

2.3.6. Relief F feature selection

ReliefF is a popular and effective feature selection algorithm for ML modeling (Urbanowicz et al., 2018). It is beneficial for problems involving classification or regression, where the goal is to select a subset of relevant features from a larger set. The main objective of this method is to identify and prioritize the most informative features that contribute the most to the prediction or target variable. It accomplishes this by estimating feature quality based on their ability to distinguish between instances of different classes or regression targets (Abdulrazaq et al., 2021).

Relief F is operated by calculating a relevance score (average merit) for each feature, indicating its importance in the classification or regression process (Mahmood et al., 2022). Relief F accounts for both the individual feature's relevance and its interactions with other features. This is accomplished by comparing the feature values of a randomly selected instance with those of its nearest neighbors, both within and across classes (Shukla et al., 2020). It assigns higher scores to features that have consistent values within instances of the same class and different values across instances of various classes (Mahmood et al., 2022). The intuition behind this is that features with significant differences in values between instances of different classes are likely to be more discriminative and informative. By selecting a subset of relevant features using Relief F, one can potentially improve the performance of machine learning models by reducing overfitting, enhancing interpretability, and speeding up training and prediction (Shukla et al., 2020).

In this work, ReliefF was used to validate and select the important input variables for predicting TBC in PSCP using various ML models.

2.4. Methodological flowchart

The methodology employed in this study is shown in Fig. 1. In the first step, a database containing 12 input variables (X1-X12) and one output variable (Y) was collected and constructed. In the second step, the database was randomly split into two parts: a training dataset (70%) and a test dataset (30%) for training and validation, respectively. In the third step, the ML models (REPT, GP, ANN, CG-GP, and CG-ANN) were constructed using the training dataset. Of these, two hybrid ML models, CG-GP and CG-ANN, were built by combining CG optimization with the single ML models GP and ANN, respectively. In these two hybrid models, CG was used to optimize the original training dataset, and the resulting optimal dataset was used for prediction with GP and ANN algorithms. In the final step, the testing dataset was used to validate the models using standard statistical measures: R^2, MAE, and RMSE to find the best model for the prediction.

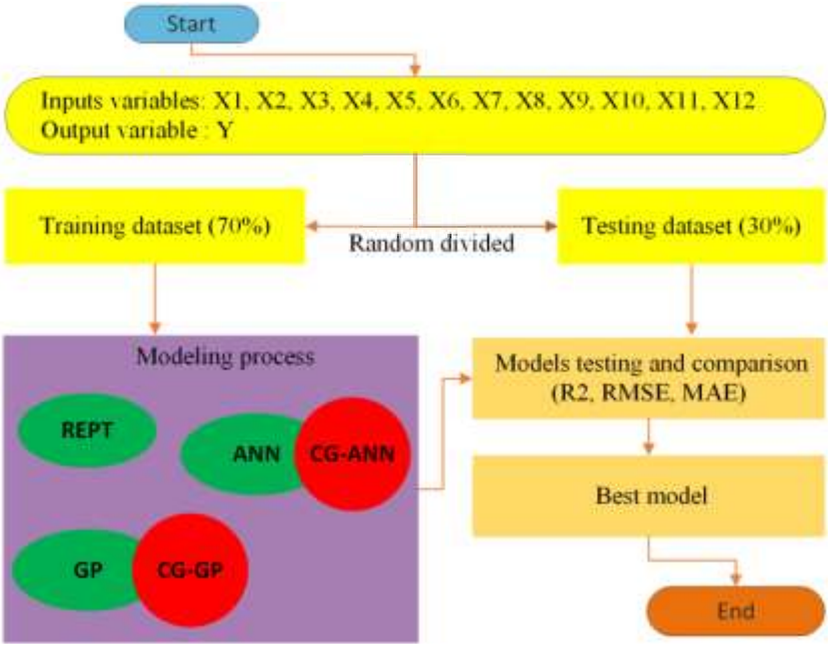

Figure 1. Methodological framework of models' study

3. Results and discussion

3.1. Feature selection based on Relief F

Relief F was used to validate the importance of the input variables used in the modeling. The feature selection results are shown in Fig. 2. It can be observed that out of 12 input variables X3 (average merit = 0.072) is the most essential input variable in predictive modeling of the TBC of PSCP, followed by X10 (0.045), X9 (0.044), X7 (0.041), X5 (0.034), X8 (0.029), X2 (0.024), X6 (0.015), X11 (0.014), X1 (0.013), X12 (0.008), and X4 (0.004), respectively. It can be stated that all 12 input variables contributed to predictive modeling and were thus retained to predict the TBC of PSCP.

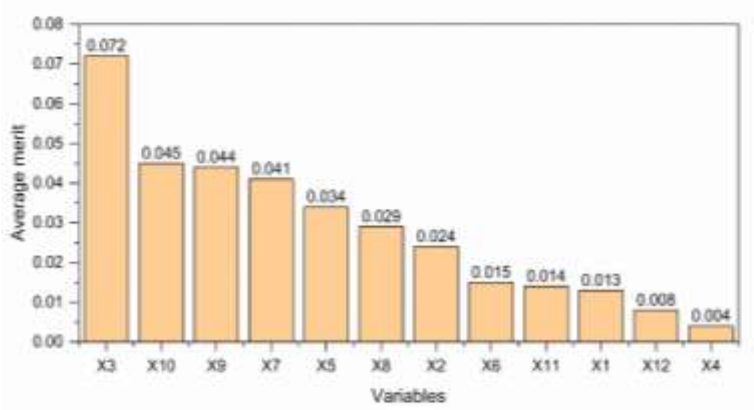

Figure 2. Importance of the input variables used in the modeling using Relief F

3.2. Evaluation and comparison of the ML models

In the present study, five ML models, namely REPT, GP, ANN, CG-GP, and CG-ANN, were used to estimate the TBC of PSCP. Among these, the novel hybrid models CG-GP and CG-ANN were developed by integrating cascade generalization (CG) with two single ML techniques (GP and ANN), respectively. The hyperparameters used to train the models are given in Table 3.

Model performance was evaluated using quantitative validation indicators, namely RMSE, R^2, and MAE, for both training and testing datasets. Performance on the training dataset reflects the goodness of fit, whereas performance on the testing dataset reflects the predictive capability of the models. The validation results are illustrated in Figs. 3–6. Figure 3 compares the predicted and actual TBC values, showing that the model-predicted values are closely aligned with the experimentally determined values. Figure 4 presents the R^2 values for the five models on the training and test datasets. Using the training dataset, the CG-ANN model achieved the highest R^2 value (0.937), followed by ANN (0.926), CG-GP (0.861), GP (0.847), and REPT (0.818). Similarly, using the testing dataset, the CG-ANN model again showed the highest R^2 value (0.935), followed by CG-GP (0.929), ANN (0.926), GP (0.916), and REPT (0.776). Figure 5 shows the distribution of error values, while Figure 6 compares R^2, RMSE, and MAE across all models for both training and test datasets. These figures clearly indicate that the CG-ANN model has the lowest RMSE and MAE, confirming its superior predictive performance compared with CG-GP, ANN, GP, and REPT.

Generally, the performance of all five ML models used for predicting the TBC of PSCP in this study is satisfactory; however, the novel hybrid CG-ANN model demonstrated the best overall performance, followed by CG-GP, ANN, GP, and REPT, respectively. The hybrid models CG-ANN and CG-GP significantly improved the predictive capability of the corresponding single models (ANN and GP). This improvement is attributed to the cascade generalization framework, which effectively reduces prediction bias and enhances model flexibility by combining the strengths of multiple learners while minimizing individual model weaknesses (Gama et al., 2000a). In addition, cascade generalization helps mitigate overfitting by progressively increasing model complexity, rather than relying on a single highly complex model. The comparison with previously published studies further indicates that the proposed CG-ANN model outperforms conventional ANN-based approaches used for predicting the bearing capacity of driven piles in cohesionless soils (Kiefa, 1998).

Table 3. Hyperparameters of the models used in the training process

No.	**Hyper-parameters**	**Models**				
		REPT	**ANN**	**GP**	**CG-GP**	**CG-ANN**
1	Do not check capabilities	FALSE	FALSE	FALSE	FALSE	FALSE
2	Initial Count	0	-	-	-	-
3	Max depth	-1	-	-	-	-
4	Min variance prop	0.001	-	-	-	-
5	No pruning	FALSE	-	-	-	-
6	Filter type	-	-	Normalize training data	-	-
7	Kernel	-	-	Poly Kernel	-	-
8	Num folds	3	-	-	5	5
9	Concatenate predictions	-	-	-	TRUE	TRUE
10	Noise	-	-	1	-	-
11	Keep original	-	-	-	TRUE	TRUE
12	Min num	2	-	-	-	-
13	Batch size	100	100	100	100	100
14	Meta classifier	-	-	-	Gaussian processes	Gaussian processes
15	Num execution slots	-	-	-	1	1
16	Seed	1	1	1	1	1
17	Spread initial count	FALSE	-	-	-	-
18	Num decimal places	2	200	2	2	2
19	Debug	FALSE	FALSE	FALSE	FALSE	FALSE
20	Activation function	-	Approximate sigmoid	-	-	-
21	Loss function	-	Square error	-	-	-
22	Num function	-	2	-	-	-
23	Pool size	-	1	-	-	-
24	Tolerance	-	0.0001	-	-	-
25	Use CGD	-	FALSE	-	-	-
26	Ridge	-	0.9	-	-	-
27	Num threads	-	1	-	-	-
28	Use log odds	-	-	-	TRUE	TRUE

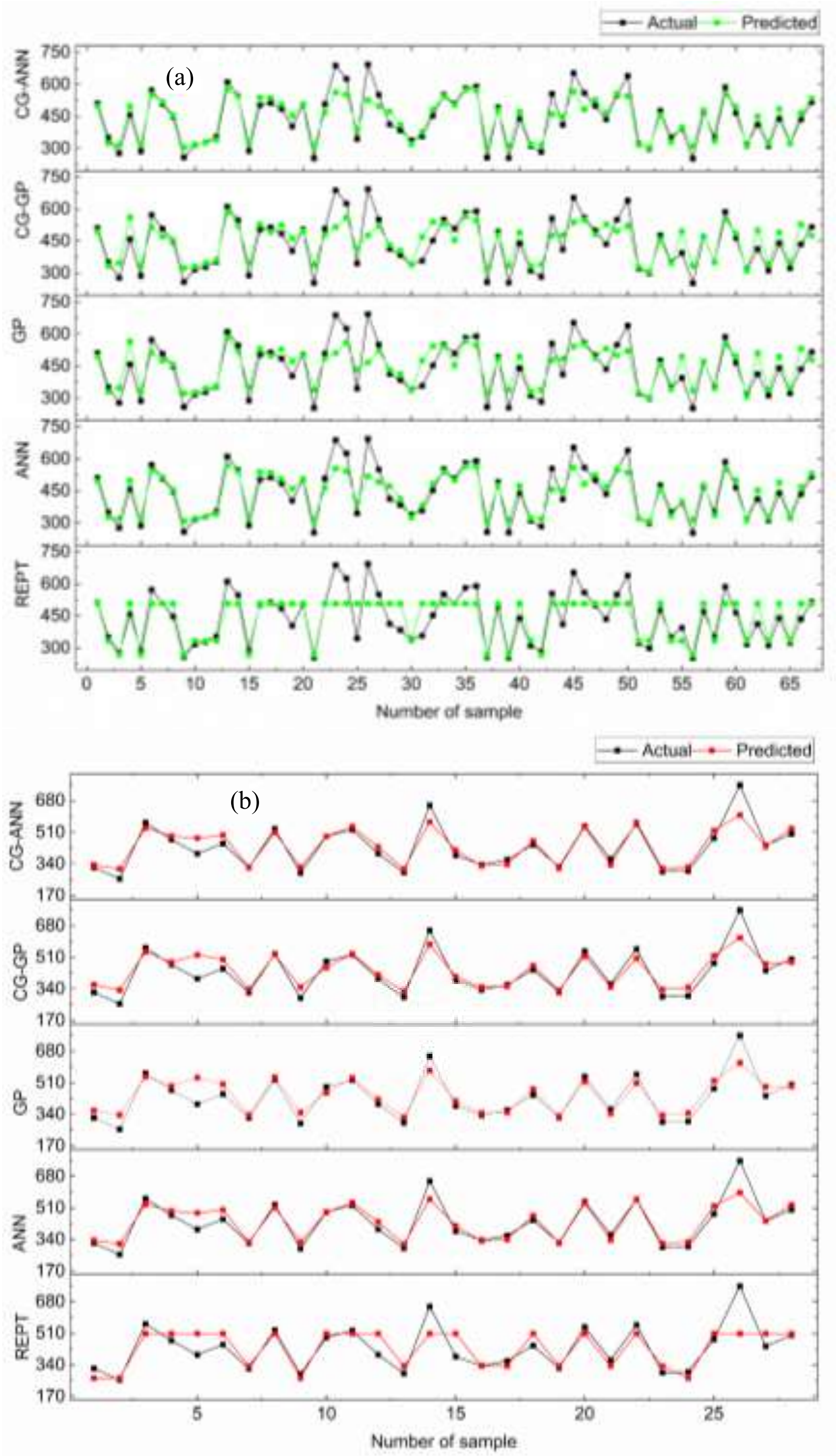

Figure 3. Comparison of predicted and actual results of different models: (a) training process and (b) testing process

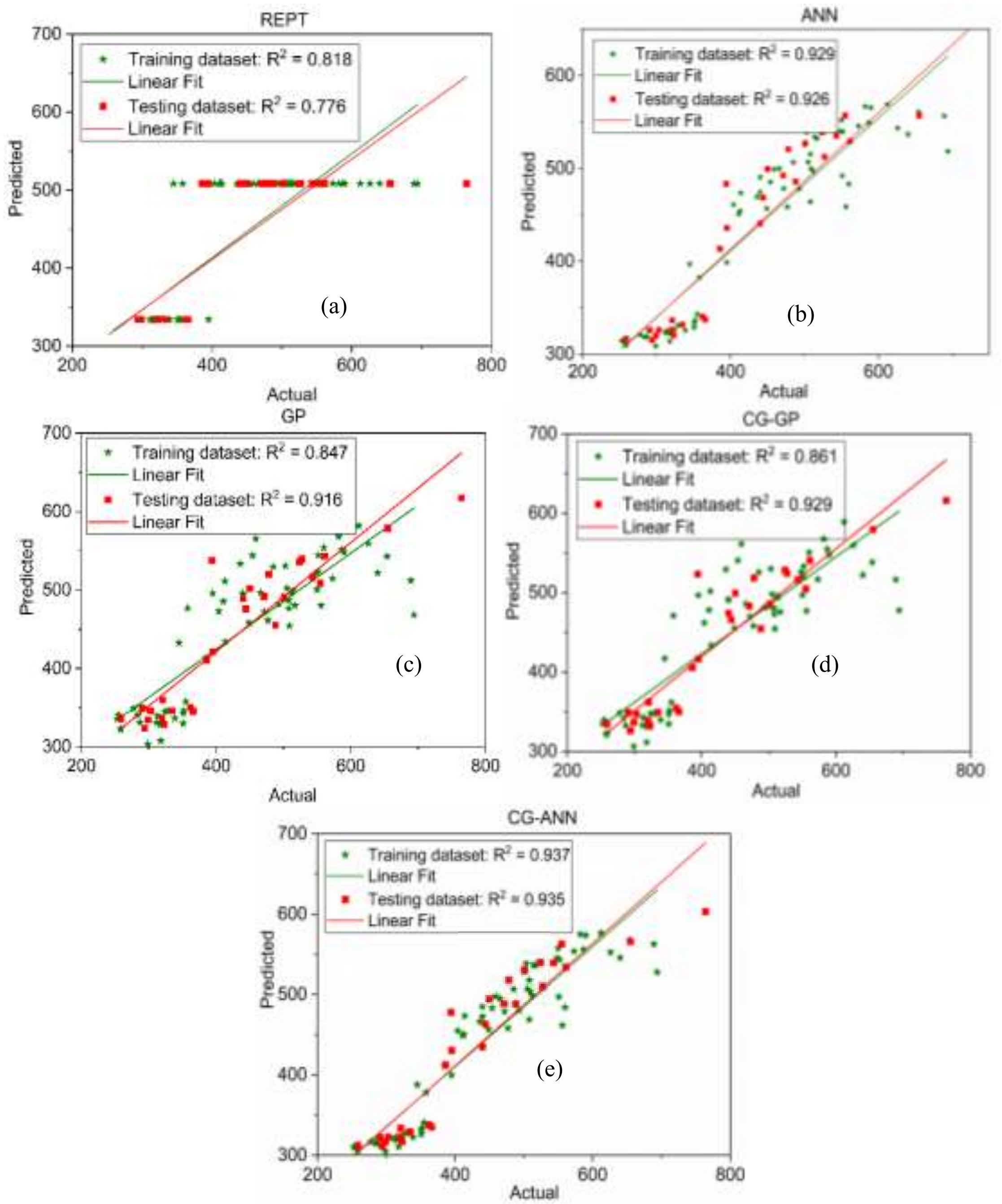

Figure 4. R^2 values of five models: (a) REPT; (b) ANN; (c) GP; (d) CG-GP, and (e) CG-ANN

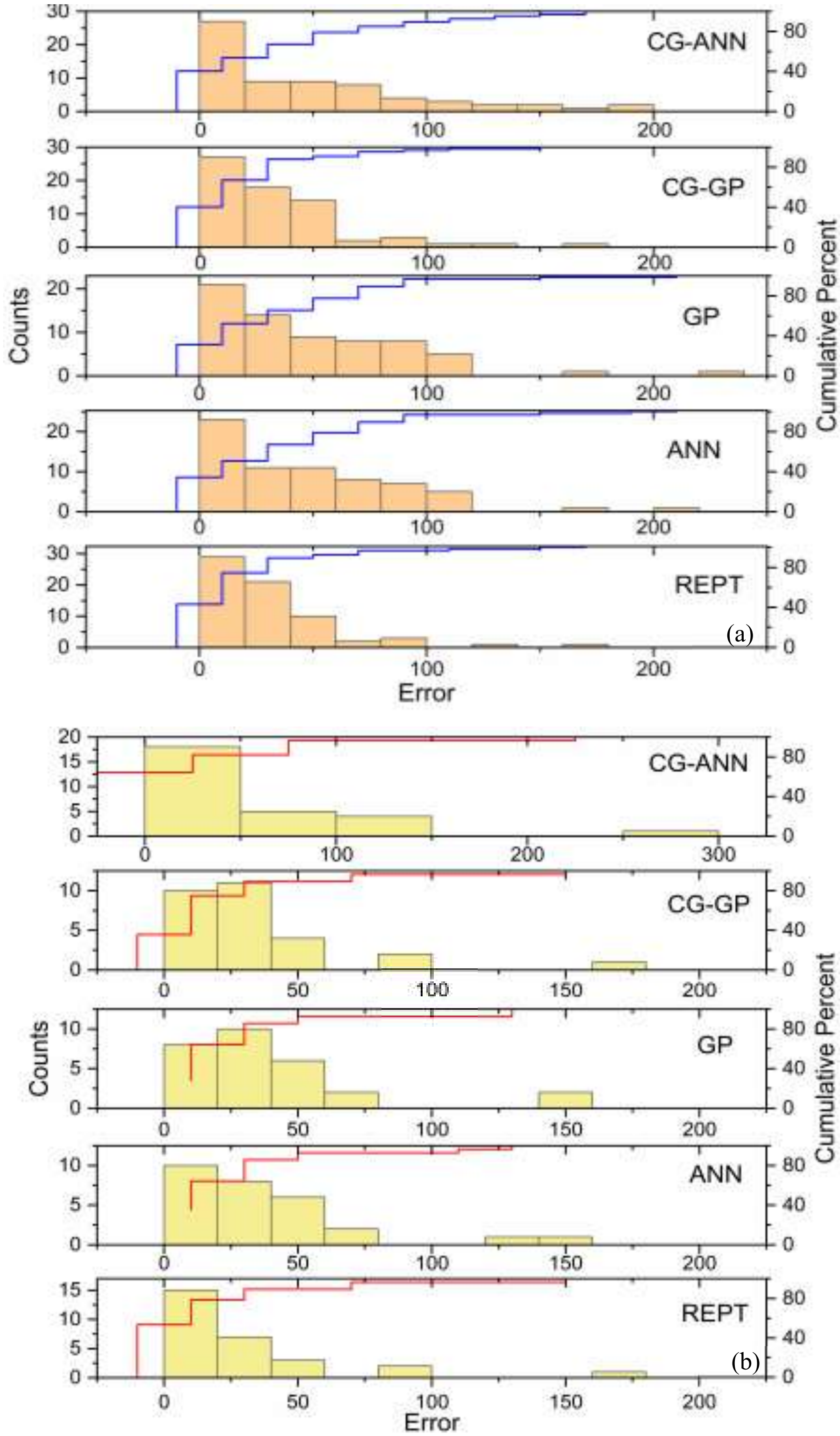

Figure 5. Distribution of error values of the models: (a) training process and (b) testing process

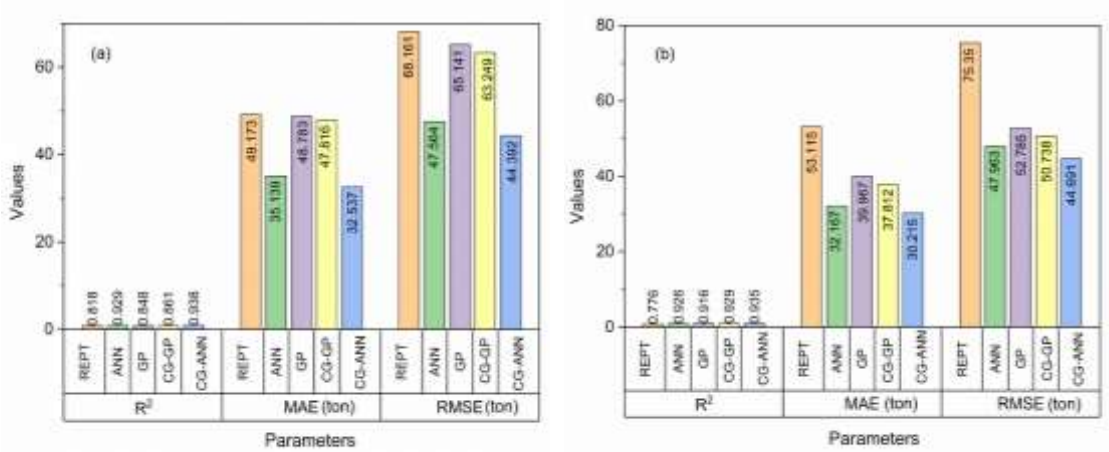

Figure 6. Comparison of the R^2, MAE, and RMSE values of five models:
(a) training process and (b) testing process

4. Conclusions

In building and bridge construction, PSCP are commonly used to transfer the superstructure's load to competent subsoil or rock. Therefore, accurate and rapid prediction of the total bearing capacity (TBC) of PSCP is essential for safe, economical, and time-efficient design and construction. Conventional field tests, such as Pile Driving Analyzer (PDA) tests, are specialized, time-consuming, and costly. To address this limitation, the present study applied three individual ML models (REPT, GP, and ANN) and two advanced hybrid models (CG-ANN and CG-GP) to predict the TBC of PSCP using 12 easily measurable physical and physico-mechanical pile parameters.

The results of the statistical performance evaluation demonstrated that the novel hybrid CG-ANN model consistently outperformed all other models, achieving the highest prediction accuracy (R^2 = 0.935, RMSE ≈ 44 tons, MAE ≈ 31 ton). This confirms the robustness and effectiveness of the CG-ANN approach for reliably estimating PSCP bearing capacity with limited input data, thereby reducing reliance on extensive field testing. The findings highlight the practical applicability of hybrid ML techniques in pile foundation engineering.

Although the CG-ANN model showed excellent performance in this study, its application to diverse geological and site conditions with larger datasets is recommended to enhance its generalization capability. In addition, incorporating K-fold cross-validation and refining input parameters may further improve model reliability and predictive performance. As machine learning model development is a continuous process, future studies may explore and compare additional advanced algorithms to further strengthen prediction accuracy and applicability.

References

Abdulrazaq M.B., Mahmood M.R., Zeebaree S.R., Abdulwahab M.H., Zebari R.R., Sallow A.B., 2021. An analytical appraisal of supervised classifiers' performance on facial expression recognition based on relief-F feature selection. In Journal of Physics: Conference Series. IOP Publishing, 1804(1), 012055. https://doi.org/10.1088/1742-6596/1804/1/012055.

Alkroosh I.S., Bahadori M., Nikraz H., Bahadori A., 2015. Regressive approach for predicting bearing capacity of bored piles from cone penetration test data. Journal of Rock Mechanics and

Geotechnical Engineering, 7(5), 584−592. https://doi.org/10.1016/j.jrmge.2015.06.011.

Ambikasaran S., Foreman-Mackey D., Greengard L., Hogg D.W., O'Neil M., 2015. Fast direct methods for Gaussian processes. IEEE transactions on pattern analysis and machine intelligence, 38(2), 252−265. https://doi.org/10.1109/TPAMI.2015.2448083.

Anitescu C., Atroshchenko E., Alajlan N., Rabczuk T., 2019. Artificial neural network methods for the solution of second order boundary value problems. Computers, Materials and Continua, 59(1), 345−359. https://doi.org/10.32604/cmc.2019.06641.

Armaghani J.D., Shoib R.S.N.S.B.R., Faizi K., Rashid A.S.A., 2017. Developing a hybrid PSO-ANN model for estimating the ultimate bearing capacity of rock-socketed piles. Neural Computing and Applications, 28(2), 391−405. https://doi.org/10.1007/s00521-015-2072-z.

Chen W., Hong H., Li S., Shahabi H., Wang Y., Wang X., Ahmad B.B., 2019. Flood susceptibility modelling using novel hybrid approach of reduced-error pruning trees with bagging and random subspace ensembles. Journal of Hydrology, 575, 864−873. https://doi.org/10.1016/j.jhydrol.2019.05.089.

Christie D., Neill S.P., 2022. Measuring and observing the ocean renewable energy resource. Comprehensive Renewable Energy, 8, 149−175. https://doi.org/10.1016/B978-0-12-819727-1.00083-2.

Daud N.R., Corne D.W., 2009. Human readable rule induction in medical data mining. In Proceedings of the European Computing Conference. Boston, MA: Springer US, 1, 787−798. https://doi.org/10.1007/978-0-387-84814-3_79.

Duc N.D., Nguyen M.D., Prakash I., Van H.N., Van Le H., Thai P.B., 2025. Prediction of safety factor for slope stability using machine learning models. Vietnam Journal of Earth Sciences, 47(2), 182–200. https://doi.org/10.15625/2615-9783/22196.

Fatehnia M., Amirinia G., 2018. A review of genetic programming and artificial neural network applications in pile foundations. International Journal of Geo-Engineering, 9(1), 2. https://doi.org/10.1186/s40703-017-0067-6.

Gama J., Brazdil P., 2000. Cascade generalization. Machine learning, 41(3), 315−343. https://doi.org/10.1023/A:1007652114878.

García J.A., Fdez-Valdivia J., Rodriguez-Sanchez R., Fdez-Vidal X.R., 2002. Performance of the Kullback-Leibler information gain for predicting image fidelity. In 2002 International Conference on Pattern Recognition. IEEE, 3, 843−848. https://doi.org/10.1109/ICPR.2002.1048156.

Gravare C.J., et al., 1980. Pile driving construction control by the Case method, 17(5), 1−94. https://doi.org/10.1016/0148-9062(80)90977-8.

Guo H., Zhuang X., Chen P., Alajlan N., Rabczuk T., 2022. Analysis of three-dimensional potential problems in non-homogeneous media with physics-informed deep collocation method using material transfer learning and sensitivity analysis. Engineering with Computers, 38(6), 5423−5444. https://doi.org/10.1007/s00366-022-01633-6.

Guo H., Zhuang X., Chen P., Alajlan N., Rabczuk T., 2022b. Stochastic deep collocation method based on neural architecture search and transfer learning for heterogeneous porous media. Engineering with Computers, 38(6), 5173−5198. https://doi.org/10.1007/s00366-021-01586-2.

Guo H., Zhuang X., Rabczuk T., 2019. A Deep Collocation Method for the Bending Analysis of Kirchhoff Plate. Computers, Materials & Continua, 59(2), 433−456. Retrieved from https://doi.org/10.48550/arXiv.2102.02617.

Harandizadeh H., Jahed Armaghani D., Khari M., 2021. A new development of ANFIS-GMDH optimized by PSO to predict pile bearing capacity based on experimental datasets. Engineering with Computers, 37(1), 685−700. https://doi.org/10.1007/s00366-019-00849-3.

Hopfield J.J.J.I.C., Magazine D., 1988. Artificial Neural Networks, IEEE, 4(5), 3−10. https://doi.org/10.1109/101.8118.

Jayanthi S., Sasikala S.J.I., 2013. Reptree classifier for identifying link spam in web search engines, 3(2), 498−505. https://doi.org/10.21917/ijsc.2013.0075.

Kiefa M.A., 1998. General regression neural networks for driven piles in cohesionless soils. Journal of Geotechnical and Geoenvironmental Engineering, 124(12), 1177−1185. https://doi.org/10.1061/(ASCE)1090-0241(1998)124:12(1177).

Kraipeerapun P., Amornsamankul S., 2019. Using cascade generalization and neural networks to select cryotherapy method for warts. Paper presented at the 2019 International Conference on Engineering, Science, and Industrial Applications (ICESI). IEEE, 1−5. https://doi.org/10.1109/ICESI.2019.8863021.

Krogh A., 2008. What are artificial neural networks?. Nature biotechnology, 26(2), 195−197. https://doi.org/10.1038/nbt1386.

Le T.-H., Nguyen H.-L., Pham C.-T., 2022. Artificial intelligence approach to predict the dynamic modulus of asphalt concrete mixtures. Journal of Science and Transport Technology, 2(2) 22−30. https://doi.org/10.58845/jstt.utt.2022.en.2.2.22-30.

Likins G.E., Hussein M., 1988. A summary of the pile driving analyzer capacity methods, past and present. In Proc., 11th Pile Driving Analyzer User's Seminar, 1−23.

MacKay D.J., 2003. Information theory, inference and learning algorithms. Cambridge University Press. 624p.

Mahmood M.R., Abdulrazzaq M.B., 2022. Performance evaluation of chi-square and relief-F feature selection for facial expression recognition. Indonesian Journal of Electrical Engineering and Computer Science, 27(3), 1470−1478. https://doi.org/10.11591/ijeecs.v27.i3.pp1470-1478.

Meyerhof G.G., 1976. Bearing capacity and settlement of pile foundations. Journal of the Geotechnical Engineering Division, 102(3), 197−228. https://doi.org/10.1061/AJGEB6.0000243.

Mitchell T.M., 1997. Artificial neural networks. Machine learning, 45(81), 127. https://www.cs.cmu.edu/~tom/mlbook.html.

Mohamed W.N.H.W., Salleh M.N.M., Omar A.H., 2012. A comparative study of reduced error pruning method in decision tree algorithms. IEEE International conference on control system, computing and engineering, 1(1) 392−397. https://doi.org/10.1109/ICCSCE.2012.6487177.

Momeni E., Nazir R., Armaghani D.J., Maizir H., 2014. Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN. Measurement, 57, 122−131. https://doi.org/10.1016/j.measurement.2014.08.007.

Montgomery D.C., Peck E.A., Vining G.G., 2021. Introduction to linear regression analysis. John Wiley & Sons.

Neal R.M., 1996. Bayesian learning for neural networks. Springer Science & Business Media, 118. https://doi.org/10.1007/978-1-1-4612-0745-0.

Nguyen D.D., Nguyen H.P., Vu D.Q., Prakash I., Pham B.T., 2023. Using GA-ANFIS machine learning model for forecasting the load bearing capacity of driven piles. Journal of Science and Transport Technology, 3(2), 26−33. https://doi.org/10.58845/jstt.utt.2023.en.3.2.26-33.

Nguyen T.T., Nguyen D.D., Nguyen S.D., Prakash I., Van Tran P., Pham B.T., 2022. Forecasting construction price index using artificial intelligence models: support vector machines and radial basis function neural network. Journal of Science and Transport Technology, 2(4), 9−19. https://doi.org/10.58845/jstt.utt.2022.en.2.4.9-19.

Omran B.A., Chen Q., Jin R., 2016. Comparison of data mining techniques for predicting compressive strength of environmentally friendly concrete. Journal of Computing in Civil Engineering, 30(6), 04016029. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000596.

Pham B.T., Amiri M., Nguyen M.D., Ngo T.Q., Nguyen K.T., Tran H.T., Hoang V., Bui T.Q.A., Le V.H., Prakash I., 2021. Estimation of shear strength parameters of soil using Optimized Inference Intelligence System. Vietnam Journal of Earth Sciences, 43(2), 189−198. https://doi.org/10.15625/2615-9783/15926.

Quinlan J.R., 1987. Simplifying decision trees. International journal of man-machine studies, 27(3), 221−234. https://doi.org/10.1016/S0020-7373(87)80053-6.

Rehamnia I., Benlaoukli B., Chouireb M., Prakash I., Amiri M., Pham B.T., 2023. Estimation of seepage flow using optimized artificial intelligent models. Geotechnical and Geological Engineering, 41(4), 2727−2739. https://doi.org/10.1007/s10706-023-02423-7.

Ren J., Xu Q., Chen G., Yu X., Gong S., Lu Y., 2023. Seismic performance of pretensioned centrifugal spun concrete piles with steel strands. In Structures. Elsevier, 50, 1303−1319. https://doi.org/10.1016/j.istruc.2023.02.107.

Shukla A.K., Pippal S.K., Gupta S., Ramachandra Reddy B., Tripathi D.J.J.o.I., Systems F., 2020. Knowledge discovery in medical and biological datasets by integration of Relief-F and correlation feature selection techniques, 38(5), 6637−6648. https://doi.org/10.3233/JIFS-179743.

Shukla A.K., Pippal S.K., Gupta S., Ramachandra Reddy B., Tripathi D., 2020. Knowledge discovery in medical and biological datasets by integration of Relief-F and correlation feature selection techniques. Journal of Intelligent & Fuzzy Systems, 38(5), 6637−6648. https://doi.org/10.3233/JIFS-1797.

Tarawneh B., 2013. Pipe pile setup: database and prediction model using artificial neural network. Soils and Foundations, 53(4), 607−615. https://doi.org/10.1016/j.sandf.2013.06.011.

Thai P.B., Nguyen D.D., Thi Q.-A.B., Nguyen M.D., Vu T.T., Prakash I., 2022. Estimation of load-bearing capacity of bored piles using machine learning models. Vietnam Journal of Earth Sciences, 44(4), 470−480. https://doi.org/10.15625/2615-9783/17177.

Urbanowicz R.J., Meeker M., La Cava W., Olson R.S., Moore J.H., 2018. Relief-based feature selection: Introduction and review. Journal of Biomedical Informatics, 85, 189−203. https://doi.org/10.1016/j.jbi.2018.07.014.

Van Le M., Prakash I., Nguyen D.D., 2023. Predicting load-deflection of composite concrete bridges using machine learning models. Journal of Science and Transport Technology, 3(4), 43−51. https://doi.org/10.58845/jstt.utt.2023.en.3.4.43-51.

Vu D.Q., Nguyen D.D., Bui Q.A.T., Trong D.K., Prakash I., Pham B.T., 2021. Estimation of California bearing ratio of soils using random forest based machine learning. Journal of Science and Transport Technology, 1(1), 45−58. https://doi.org/10.58845/jstt.utt.2021.en.1.1.45-58.

Rasmussen C.E., Williams C.K., 2006. Gaussian processes for machine learning: MIT press Cambridge, 266p. https://mitpress.mit.edu/9780262182539.

Yong W., Zhou J., Jahed Armaghani D., Tahir M., Tarinejad R., Pham B.T., Van Huynh V., 2021. A new hybrid simulated annealing-based genetic programming technique to predict the ultimate bearing capacity of piles. Engineering with Computers, 37(3), 2111−2127. https://doi.org/10.1007/s00366-019-00932-9.

Zhao H., Ram S., 2004. Constrained cascade generalization of decision trees. IEEE Transactions on Knowledge and Data Engineering, 16(6), 727−739. https://doi.org/10.1109/TKDE.2004.3.

Zhao Y., Zhang Y., 2008. Comparison of decision tree methods for finding active objects. Advances in Space Research, 41(12), 1955−1959. https://doi.org/10.1016/j.asr.2007.07.020.

Zhuang X., Guo H., Alajlan N., Zhu H., Rabczuk T., 2021. Deep autoencoder based energy method for the bending, vibration, and buckling analysis of Kirchhoff plates with transfer learning. European Journal of Mechanics-A/Solids, 87, 104225. https://doi.org/10.1016/j.euromechsol.2021.104225.