Research Article

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Estimation of the settlement of pile head using ANN and multivariate linear regression based on the results of load transfer method

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Abstract: Artificial neural networks, machine learning, and data preparation are normally implemented in a wide range of real-world problems, especially in geotechnical applications with optimistic prospects of accurate procedure outcomes. This technique has been utilized to precisely predict the top settlement of piles with various piles and soil parameters. Generally, the pile settlement is an essential requirement to produce a secure structure and has high-performance services. The current article presents the fitting of the artificial neural network (ANN) outcomes by calculating the coefficient of correlation R^2 between the predicted and the measured or calculated value of pile settlement. The ANN algorithm is developed using Python 3.9 IDLE and open-source libraries such as Keras, sklearn, Numpy, matplotlib, pandas, and Tensorflow. Because of random training and test performance, the model has been run at least ten times. The ANN model score and R^2 are compared for all runs in the testing phase. The higher score and R^2 values are chosen. Moreover, the Multivariate Linear Regression with the sklearn library is also offered in this article and utilized to produce a pile settlement formula by applying the same dataset used in ANN. The score and R^2 for choosing the first run of the ANN are 99.95% and 0.9631, respectively, while the correlation coefficient for the Multivariate Linear Regression in the training and testing phases is 0.972 and 0.919, respectively. Both techniques illustrate considerable results.

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1 Introduction

Deep foundations (piles) are an essential part of any structure; the basic function of these foundations is to transfer the superstructure load to a deeper and stronger bearing stratum. For common knowledge of geotechnical engineering, piles can be chosen when the use of shallow foundations is not recommended because the bearing capacity of subsurface soil is inadequate to carry the proposed building. The settlement of foundations is another basic considerable parameter. Therefore, the estimated subsoil settlement with shallow footing must be also less than the allowable settlement of such footing, otherwise, piles will be alternative footing. The vast challenge, of pile settlement calculations, is enormous uncertainty factors relevant to soil properties that affect the magnitude of the settlement [1]. Poulos [2] reviewed theoretical and experimental investigations in the last twenty to thirty years. All of these studies stated conventional methods to estimate the settlement of different foundation types (shallow and deep foundations). It was concluded that most of such methods could be adjusted or ignored. So, in terms of geotechnical engineering, the comparison between the estimated bearing capacity of a pile using ANN and several empirical formulas was achieved. The outcomes of the ANN model acceptable estimated piles bearing capacity [3–7].

2 Artificial neural networks (ANN)

Neural Networks are an immensely useful model of machine learning techniques, with countless applications for real scenario problems. The application of ANNs to solve numerous geotechnical issues becomes a frequent approach with a high degree of success, and this is because of the development of data management. ANNs are one of the most common artificial intelligent forms. The earlier study to apply ANN was introduced in 1985. This study did not reach a finished form of ANN, the recurrent networks and sigma-pi units were only investigated. Although the learning procedure for many very complex problems has not been applied, the results data promising approaches for further study [8]. Generally, ANNs could be considered a good growing tool that can be used in prediction and forecasting fields such as weather forecasting, stock markets, financial institutions, and scientific research studies. Gnananandarao *et al.* [9] confirmed the ability of ANN models to predict a complex relationship between the nonlinear data of the predicted settlement of shallow foundations on cohesionless soils. The capability of back-propagation neural networks was investigated to predict the settlement of piles with an adequate rate of accuracy in comparison with conventional methods [10,11]. For more applications of ANN models, artificial neural networks (ANNs) have been effectively applied more than the traditional methods to estimate a shallow foundation settlement on granular soils [12]. Overall, ANNs are useful and powerful implements to solve numerous field geotechnical problems [13].

Since ANNs are widely used to predict the foundation settlement, a sequential model of ANN using Python is developed to estimate the pile settlement of single axially loaded piles based on the load transfer method. This is the first objective of the current study.

3 Multivariate linear regression

Very little literature was found in geotechnical research studies utilizing Multivariate Linear Regression (MLR). However, general regression can be overviewed here. Recep [14] stated the use of multiple linear regression MLR and polynomial equations to offer an expression predicting the maximum moment across a cantilever sheet pile with a correlation coefficient of 0.971. The correlation between in situ settlement measured and predicted values using the multivariate adaptive regression splines (MARS) method showed a satisfactory relation so the study offered the highest accuracy in the regression process [14].

The evaluation of the MLR and ANN model's performance was attained by finding the coefficient of correlation R for estimation of uniaxial compressive strength (UCS) and modulus of elasticity (E) of intact rock [15]. Tarawneh and Imam [16] stated that the ANN model outperformed the Multiple Linear Regression MLR model and can be adequately utilized to predict pile setup. Furthermore, in comparison between a multilayer perceptron (MLP) of artificial neural networks and a regression model, the former model showed higher performance in the prediction of undrained cohesion intercept of fine soil than the latter model [17].

The second objective of the current article is to use multivariate linear regression (MLR) by implementing the ordinary least squares (OLS). This class can be found in the open-source library of sci-kit – learn 1.0.2. The input data set used in this algorithm is the same data set that is utilized in the ANN model. The normalization of input data is also performed to obtain more accurate outcomes. The data set is divided into 60% training (105 samples) and 40% testing (70 samples) for input data for the MLR model. The output of the model is compared with normalized pile settlement by determination of R^2 in the training and testing phases.

3.1 Data input/output

The data set for both ANN and MLR models is obtained from an unpublished numerical study relevant to the current article author. The input data set contains 175 samples, each sample has 17 parameters. These parameters are addressed as features of both models, while the resulting pile head settlement is considered the output of the models, which is named a model's target. The features represent the pile geometry as well as soil profile characteristics. Although the determination of pile settlement using the load transfer method is out of the scope of this article, some details can be presented here related to the ANN and MLR input features.

Poulos and Davis [18] revealed that the pile settlement could be calculated using the parameters of pile length, pile shaft diameter, pile base diameter, pile and soil Young's modulus, soil Poisson's ratio, rigid stratum layer depth, slenderness ratio, pile base shaft diameter ratio, pile-soil young's modulus ratio, pile embedded ratio, incompressible pile settlement factor, compressible pile correction factors, rigid stratum depth correction factor, soil Poisson's ratio correction factor, stiffness of bearing stratum correction factor, and finally, applied axial load. These 17 parameters or variables were calculated by applying various charts [18]. The settlement of the pile is the outcome of the numerical analysis based on experimental work of the tip and skin resistances of bored piles in London clay [19]. The use of numerical study results rather than the experimental investigation may be a good idea to take into account the pile geometry and soil mechanical properties in ANN inputs.

In this article, the input parameters are L_s, D_s, D_b, E_p, E_s, V_s, h, L/D_s, D_b/D_s, E_p/E_s, L/h, I_o, R_k, R_h, R_v, I, P, and the output is the pile top settlement (sett), the definition of these features or variables are presented in notation list. The features and resulting pile settlement are tabulated in columns to make the total data set include 175 samples, which are saved as a comma-delimited file to read the data using a pandas data frame. It is worth practicing to enhance the performance of ANN by improving the correlation between the input parameters, extracting the information from poor input data, and applying the ANN to develop new design approaches to geotechnical problems [20].

3.2 Data cleaning

Despite the ANNs being powerful models, the uncertainties related to the measurement of geotechnical parameters should be essentially treated to obtain more realistic results [13]. Therefore, before entering the ANN or MLR model, data cleaning is an effective step in any machine-learning model to improve its performance [21]. For the current study, the data set of pile geometry and soil profile characteristics is prepared in a spreadsheet. Various statistical analysis and data visualization approaches, such as histogram and outlier identification, can be implemented to discover the nature of data correlation. Data cleaning operations include identifying and eliminating column variables (features) that only have a single value, or very few unique values, and finally determining and removing the data set samples that contain duplicate observations [21,22].

In this investigation, four of 17 columns of parameters (features of I_o, R_k, R_h, and R_v) are manually merged in one feature I, because the values of I were already calculated dependent on I_o, R_k, R_h, and R_v as Poulos and Davis [18] stated this relationship. Some relevant features should be merged into one to boost the performance of the ANN model [21]. Consequently, 13 parameters would be entered in the ANN model instead of 17. The parameters will be only L_s, D_s, D_b, E_p, E_s, V_s, h, L/D_s, D_b/D_s, E_p/E_s, L/h, I, and P which are used as input data for the ANN and MLR models.

To understand the nature of the data and the distribution of each input and output parameter, a box and whisker, and histogram plots are presented to identify the outlier and data variation for all input and output data as shown in Figures 1 and 2. This is a beneficial practice to realize the significant influence of the different variables on the accuracy of model output [23].

4 Ann model structure

A supervisor ANN model with two hidden layers is developed using the open-source library of Keras module with

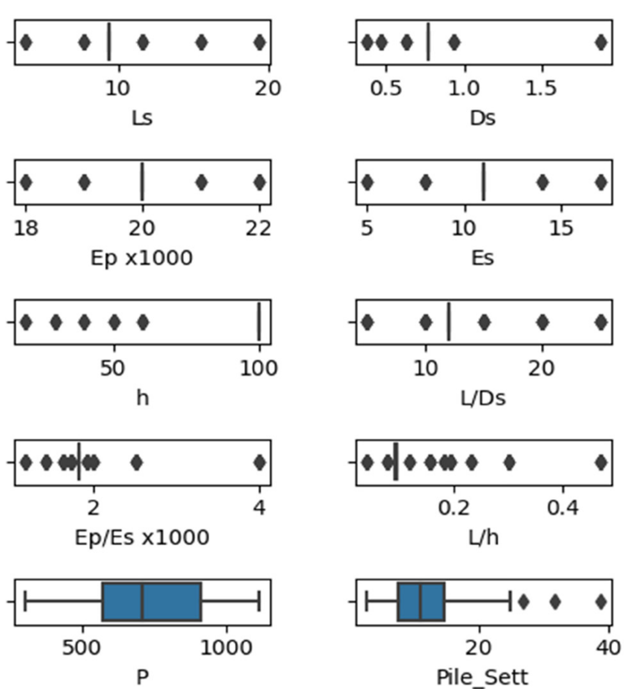

Figure 1: Box and Whisker plot input data and Pile_Sett as output data.

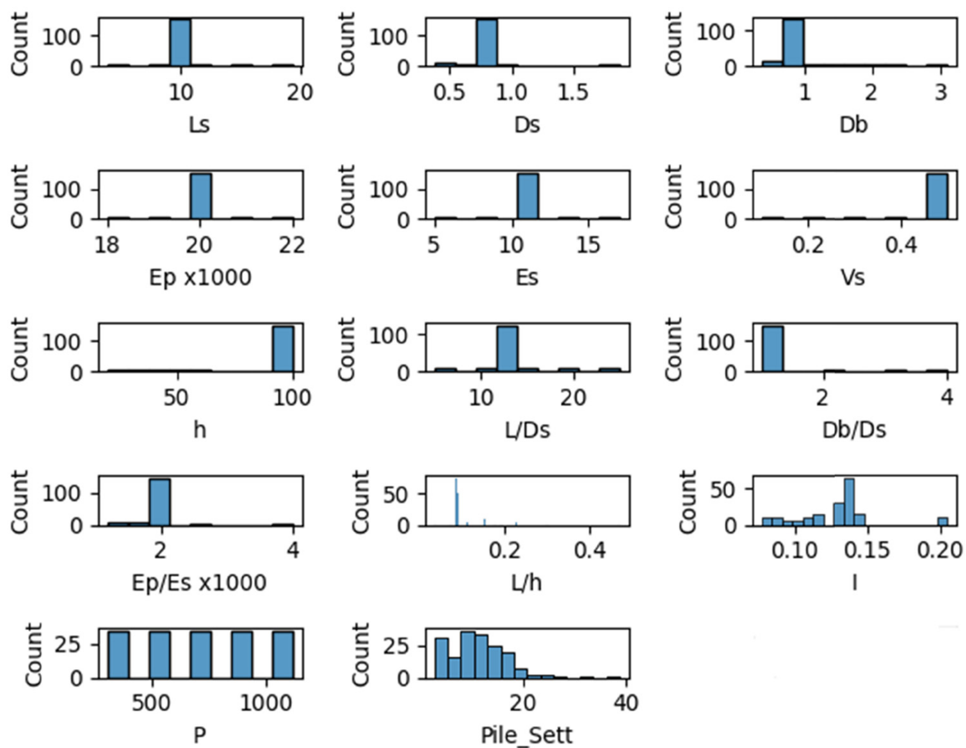

Figure 2: Histogram of input data and Pile_Sett as output data.

IDLE python 3.9, a flow chart is presented in Figure 3, and a pseudo-code is also shown in the Appendix and shows the algorithm of the model. Such a model is required to read a data set, which consists of independent parameters (features) as input data, as well as the dependent data as a target of desired data (Pile_Sett). The feature data represent pile specification, and soil properties and the target data donate measured top-head pile settlement. As mentioned earlier, these data are obtained from unpublished studies relevant to this article's author. The ANN model structure consists of an input layer, a couple of hidden layers, and an input layer, several processing elements (PE), or neurons that are usually arranged in hidden layers. In this model, each neuron in the first hidden layer is fully connected to each input parameter via its weight (randomly generated), and a threshold value (bias) is added to form a perceptron. The value of each neuron comes from the summation of the input perceptions. Before moving to the next hidden layer, the value of the neurons can be transferred using the activation function to make the Neural Network nonlinearly work. In the current ANN sequential model, the activation function E-swish is used for both hidden layers output, this function consistently outperformed other activation functions on a wide range of real-world problems and showed state of art results for different data sets [24]. This process is summarized in Figure 4.

The neurons (units) learning, of this ANN model, include training, validation, and testing. Therefore, the obtained data are divided into 60% for training, 20% for validation, and 20% for testing. The input data set (features as an array, and target as a vector) is randomly divided according to learning data division percentages. As stated above, the data set has 175 samples (a measurement set of 13 parameters). For the currently used ANN model, the E-swish function is customized, in the Keras sequential model, as an activation function [24,25]. Moreover, mean squared logarithmic error (MSLE) is chosen to be a loss function that is used to solve the regression phase as shown below. MSLE is calculated as the average of the squared differences between the log-transformed actual and predicted values. Adam optimizer is selected to reduce the error and the learning rate is 0.01, this rate shows the best model performance. For more model details, the maximum number of iterations (epoch) is 100. After taking a range of epochs 50, 80, and 100, the maximum number of 100 offers the best accuracy and good training.

$$\mathrm{MSLE} = \frac{1}{n}\sum_{i=1}^{n}(\log(y_{\mathrm{actual}i} + 1) - \log(y_{\mathrm{predict}_i} + 1)), \quad (1)$$

where n is the number of data set samples, y_{actual} is the actual value of the data set samples, and y_{predict} is the predicted value of the data set samples (the resulting value of ANN model run).

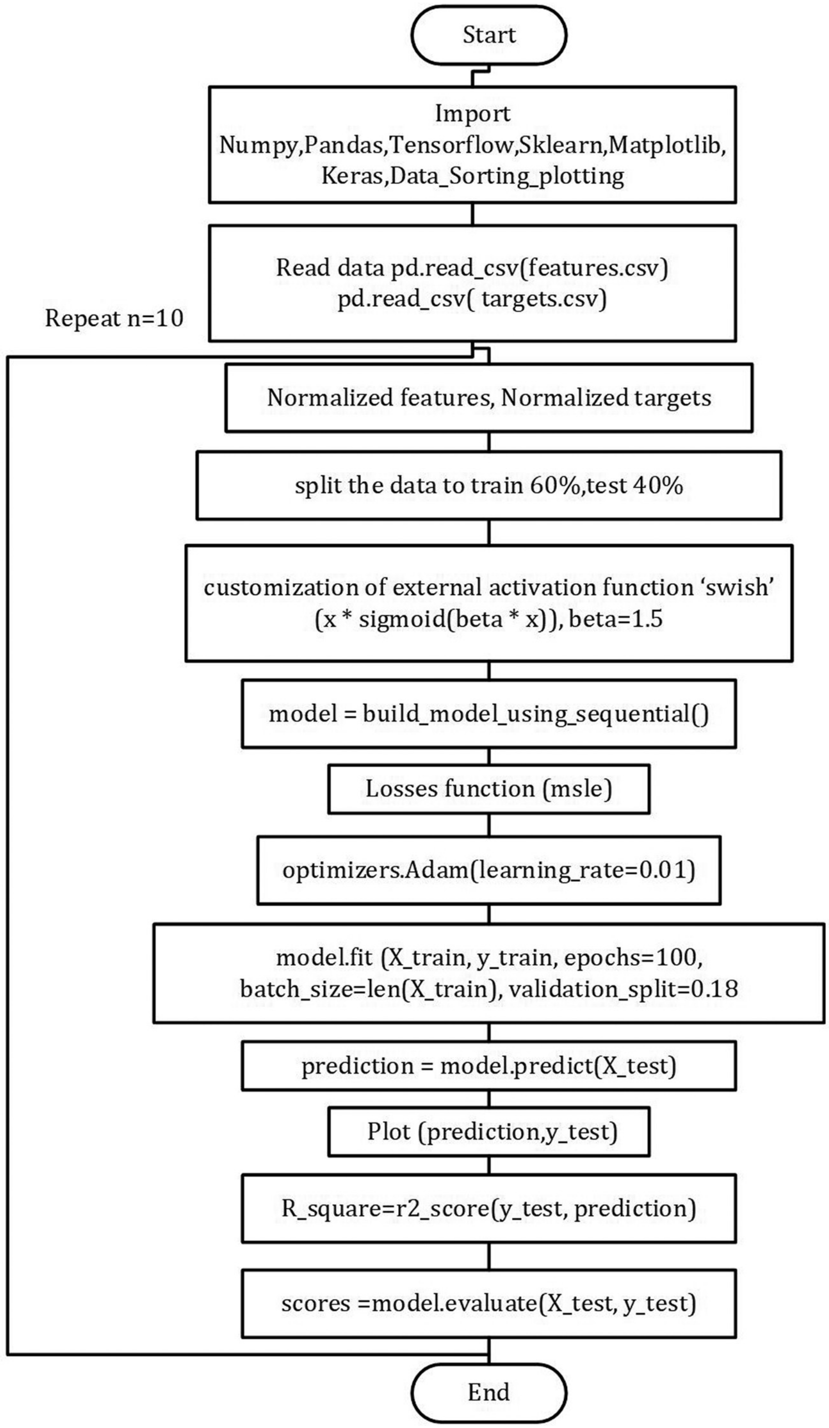

Figure 3: A flow chart of ANN algorithm.

In terms of ANN structure, the current model consists of two hidden layers, in addition to input and output layers. The number of neurons in the first hidden layer is 13, the same number of features. The sequence hidden layer (the second layer) has half the neurons (units) of the first layer (*i.e.* around six units).

Before entering the ANN model, the normalized input data set illustrates better accuracy than the standardization of such data. Therefore, the normalization of data is performed before running the model [10]. Since this model works by random data splitting and randomly generates the weight and biases for both hidden layers, this model

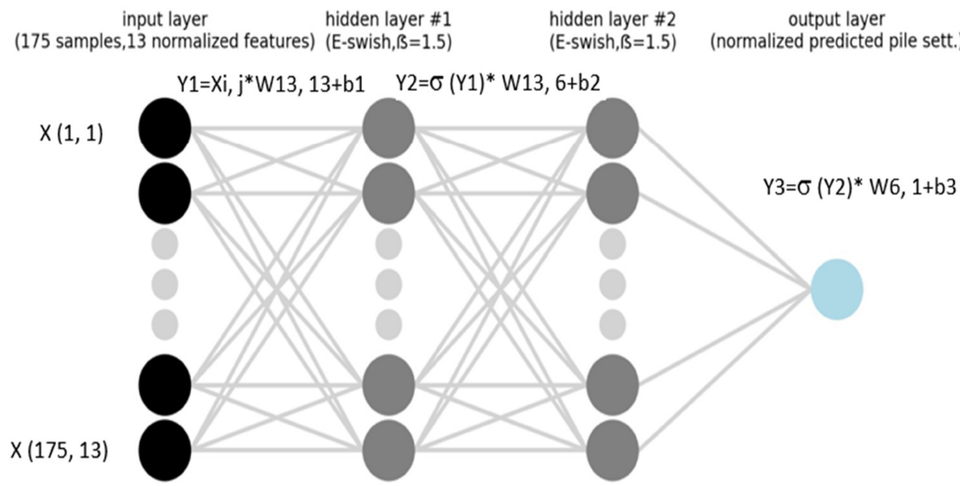

Figure 4: ANN structure.

has been run at least ten times. Subsequently, the best value of the coefficient of correlation R^2 and model accuracy has been chosen.

In this study, the data sets have been normalized between 0 and 1 for input and output data sets using the following equation:

$$\text{Normalized varibale value} = \frac{\text{the orignal variable value} - \text{minmum value of the data set}}{\text{maximum value of the dataset} - \text{minmum value of the data set}}. \quad (2)$$

5 Model validation and testing

The validation of the training phase is usually executed to confirm the phase performance so that the model effectively achieves its proposed determination. For this practice, the validation data sets have not been utilized as input data for the learning process.

The correlation coefficient R, Mean Squared Logarithmic Error (MSLE) and accuracy score are the essential criteria that are used to assess the predictive ability of the ANN model. The relative correlation between the actual or desired output and the prediction data can be measured by calculation of R^2. The Mean Squared Logarithmic Error (MSLE) is the most common cost function chosen to measure the error in the descent gradient stage.

The accuracy score for the model is also calculated and if for any reason such as randomly dividing the data set, this accuracy score is low, the ANN model is run ten times to obtain a high descent accuracy score.

6 Results and discussion

The ANN and MLR models have been run and the outcomes of both models are discussed and presented in this section.

6.1 ANN run

The ANN model is run at least ten times because the input data set is randomly divided for training, validation, and testing phases. The divided dataset may be altered at each new run. Therefore, the ANN score and the coefficient of correlation R^2 in the testing phase also show various values as shown in Figure 5.

From Figure 5, it can be noticed that the first run demonstrates the maximum values for both R^2 and the score of the ANN, they are 96.31 and 99.95% respectively. All outcomes of this run can be chosen as perfect ANN model parameters such as the weights and biases for all layers of connection of the ANN model.

To obtain the optimal values of the parameters, the minimum value of the chosen loss function is calculated by the iterative running of the gradient descent technique. Mathematically, this technique is the derivative of the loss function to attain the minimum point. Learning rate is the size of the derivative step that offers some additional control over how large steps can be made. Despite the large step requiring less time consuming, the desired lowest point could be overshot. Whereas a low learning rate is more precise, the gradient descent takes a very long time to

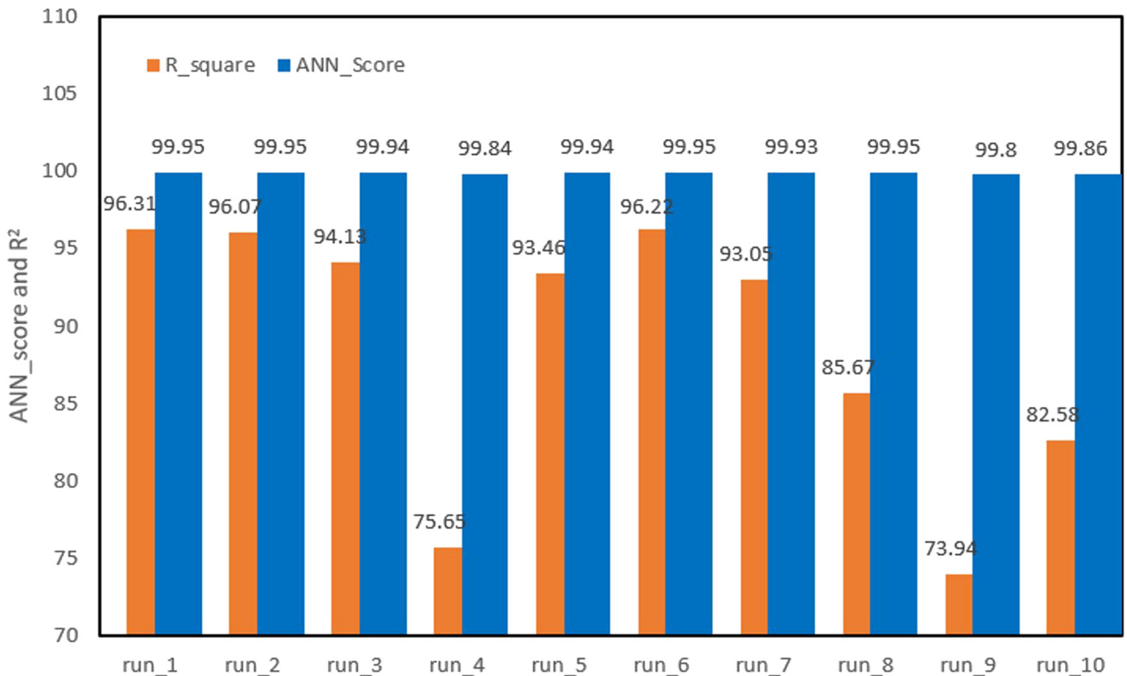

Figure 5: ANN Score and R^2 at the testing phase.

reach the minimum slope of the loss function [24]. Therefore, the used learning rate in this model is 0.01, this rate is commonly utilized [26]. Figure 6 depicts the gradient descent of the loss function for the training and testing phases. It can be noticed that the losses reach the lowest point when the iteration ranges from 80 to 100.

The plot of the measured (target) and predicted settlement for the testing set for the ANN model are shown in Figure 7. The correlation coefficient is 0.963.

The weight of each parameter for the optimal ANN model (best results) can be shown for comparison purposes. To avoid presenting too much information, only the first neuron for each layer is illustrated. The change of each parameter percentage participates in calculating the first neuron value in the first and second hidden layers (Figure 8a and b). For example, the participation percentage of the applied vertical load (P) is 32% in the first neuron of the first hidden layer, whereas this percentage drops to 3% in the first neuron of the second hidden layer. It can be observed that the percentage change of other parameters for the mentioned neurons is illustrated in Figure 8.

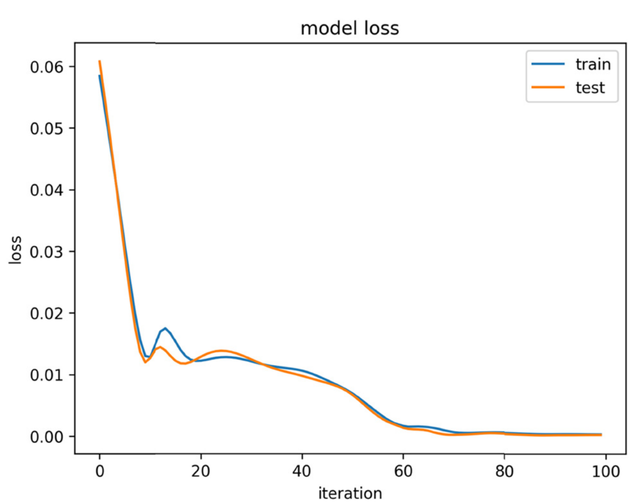

Figure 6: ANN model loss in training and testing phases.

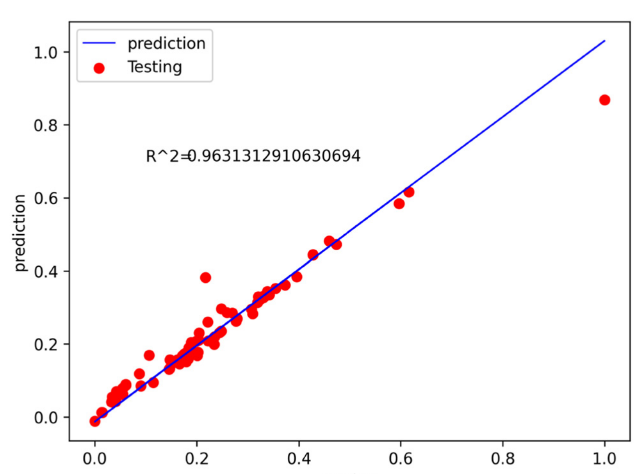

Figure 7: The predicted and testing normalized pile top settlement.

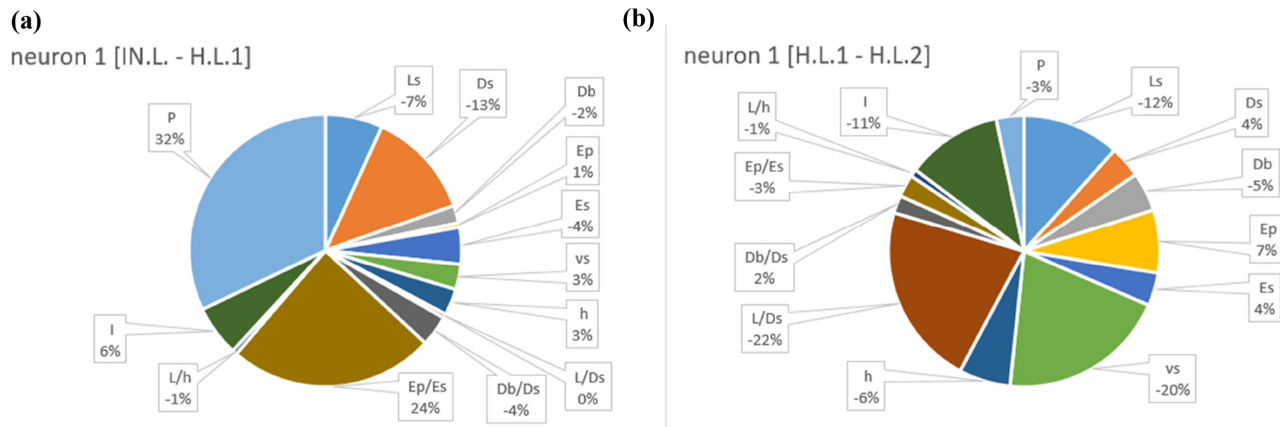

Figure 8: (a) The first neuron of the first hidden layer and (b) the first neuron of the second hidden layer.

Figure 9 shows the percentage of each of the six weights (portions) to predict the normalized pile settlement in the output layer. Each portion was formed by various percentages of all parameters.

6.2 MLR run

A linear mathematical model is formed in this section. Therefore, the multivariate linear regression is run using the same data set which is used in the ANN model. All features are also normalized before running the MLR model. The data is divided into 60% for the training phase and 40% for the testing phase.

Figure 10 depicts the correlation between the normalized training pile settlement from the data set which is defined as measured pile settlement and the prediction of normalized pile settlement using Multivariate Linear Regression MLR. This regression offers a coefficient of determination R^2 of 0.972 and Intercept of (−0.10966845).

In the testing phase, the resulting regression coefficients in the training phase are used with normalized features of the testing phase to estimate the normalized pile top settlement. The following equation is presented by applying the normalized values of all independent parameters, and these parameters are detonated in a later Notation list:

$$\text{prediction\_test} = \text{coef. dot}(X\text{\_test. T}) + \text{intercept}, \quad (3)$$

or applying this model on a testing data set of 70 samples as the following

$$\begin{aligned}
\text{Normalizedpile settlement} = {} & \\
& - 0.18138084(L_s) - 0.2645253(D_s) + 0.01658562(D_b) \\
& - 0.06294832(E_p) - 0.02684476(E_s) - 0.00455433(\mathrm{V_s}) \\
& - 0.00282297(h) + 0.24802737(L/D_s) - 0.00253914(D_b/D_s) \\
& + 0.49255763(E_p/E_s) - 0.00588953(L/h) + 0.34158744(I) \\
& + 0.35446004(P).
\end{aligned} \quad (4)$$

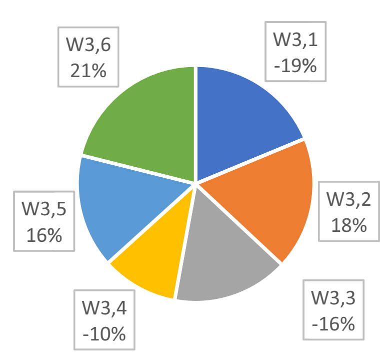

Figure 9: Output neuron with its six weights to predict pile settlement.

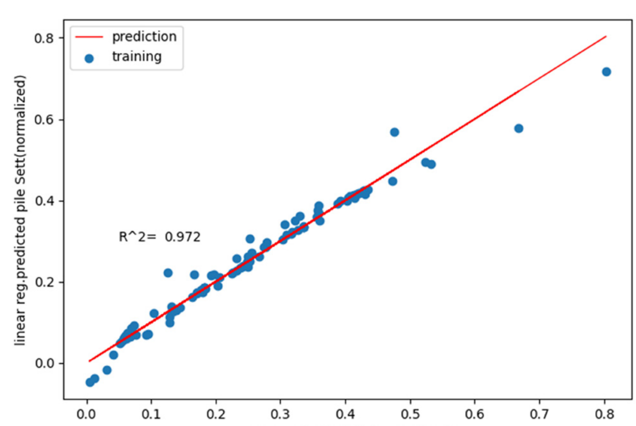

Figure 10: The correlation between the normalized training data set which is defined as measured pile settlement and the predicted normalizing pile settlement due to regression.

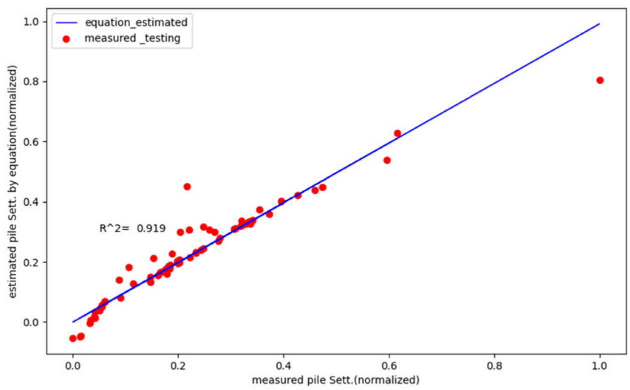

Figure 11: The correlation between the normalized testing data set which is defined as measured pile settlement and the predicted normalizing pile settlement due to regression.

Figure 11 illustrates the correlation between the normalized testing pile settlement from a data set defined as measured pile settlement and the prediction of normalized pile settlement using the mathematical equation mentioned above. The relationship shows a coefficient of determination R^2 of 0.919.

Comparisons between the results obtained from the optimal ANN model and Multivariate linear regression MLR to estimate the pile settlement are presented in this section. As shown in Figure 12, the passion's ratio, depth of rigid stratum, pile length to stratum depth ratio, and pile base diameter to shaft diameter ratio are insignificant parameters to predict normalized pile settlement. Unlike, these parameters have substantial proportions in the ANN model.

Treatment of pile problems using numerical and ANN models has been covered by several researchers [27,28]. The present study proved the capability of ANN algorithms in solving the problem of pile settlement.

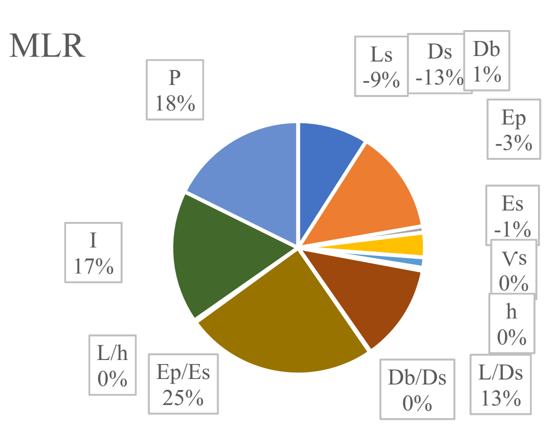

Figure 12: The participation percentages of parameters to estimate pile settlement using MLR.

7 Conclusions

Keras-sequential ANN model has been utilized to predict the top head pile settlement. This model has state of the art activation function E-swish in the transformation stage and has a loss function of mean squared logarithmic error (MSLE) in the gradient descent stage as mentioned above. The following conclusions could be obtained:

1. The results indicate that the current neural network can predict the pile top settlement with high accuracy (coefficient of determination, R^2 = 0.9631, MSLE = 1.06 mm) for anticipated settlements ranging from 2.753 to 38.786 mm.
2. The distinctively essential advantage of using the ANN model, once the model is trained, the model can predict the top head pile settlement. However, the traditional methods to calculate pile settlement, such as elastic solution and load transfer method, these methods are required using charts and tables manually to calculate pile geometry and soil properties correction factors.
3. Moreover, it is worth practicing to form a mathematical model predicting pile top head settlement using MLR which also shows a great correlation between estimated and measured pile top head settlement with R^2 = 0.919. Accordingly, in terms of machine learning, the use of MLR is promising to be applied for determining pile settlement based on input data set division.
4. Finally, as a result, the use of ANNs shows beneficial practices and powerful implementation to predict pile settlement. In the testing phase, the ANN model offers higher performance than the multiverse linear regression MLR as [16,17] reported.

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Conflict of interest: The authors state no conflict of interest.

Data availability statement: Most data sets generated and analyzed in this study are comprised in this submitted manuscript. The other data sets are available on reasonable request from the corresponding author with the attached information.

References

[1] Shahin MA. State-of-the-art review of some artificial intelligence applications in pile foundations. Geosci Front. 2016 Jan 1;7(1):33–44. doi: 10.1016/j.gsf.2014.10.002.

[2] Poulos HG. Common procedures for foundation settlement analysis: Are they adequate? In Australia-New Zealand Conference on Geomechanics (8th: 1999: Hobart, Tas.). Barton, ACT: Australian Geomechanics Society; 1999 Jan. p. 3–25.

[3] Tarawneh B. Pipe pile setup: database and prediction model using artificial neural network. Soils Found. 2013 Aug;53(4):607–15. doi: 10.1016/j.sandf.2013.06.011.

[4] Benbouras MA, Petrişor AI, Zedira H, Ghelani L, Lefilef L. Forecasting the bearing capacity of the driven piles using advanced machine-learning techniques. Appl Sci. 2021 Nov;11(22):10908. doi: 10.3390/app112210908.

[5] Pham TA, Ly HB, Tran VQ, Giap LV, Vu HL, Duong HA. Prediction of pile axial bearing capacity using artificial neural network and random forest. Appl Sci. 2020 Mar;10(5):1871. doi: 10.3390/app10051871.

[6] Jankowski W, Sołkowski J. The modelling of railway subgrade strengthening foundation on weak soils. Open Eng. 2022 Sep 2;12(1):539–54. doi: 10.1515/eng-2022-0053.

[7] Lat DC, Jais IB, Ali N, Baharom B, Mohd Yunus NZ, Mat Yusof DA. Uplift and settlement prediction model of marine clay soil e integrated with polyurethane foam. Open Eng. 2019 Nov;9(1):481–9. doi: 10.1515/eng-2019-0054.

[8] Rumelhart DE, Hinton GE, Williams RJ. Learning internal representations by error propagation, parallel distributed processing, explorations in the microstructure of cognition. Rumelhart DE, McClelland J, editors. Vol. 1, 1986. Biometrika. 1986;71:599–607.

[9] Gnananandarao T, Dutta RK, Khatri VN. Application of artificial neural network to predict the settlement of shallow foundations on cohesionless soils. In Geotechnical Applications: IGC 2016. Vol. 4, Singapore: Springer; 2019. p. 51–8. doi: 10.1007/978-981-13-0368-5_6.

[10] Alkroosh I, Nikraz H. Predicting pile dynamic capacity via application of an evolutionary algorithm. Soils Found. 2014 Apr 1;54(2):233–42. doi: 10.1016/j.sandf.2014.02.013.

[11] Nejad FP, Jaksa MB, Kakhi M, McCabe BA. Prediction of pile settlement using artificial neural networks based on standard penetration test data. Computers Geotech. 2009 Sep;36(7):1125–33. doi: 10.1016/j.compgeo.2009.04.003.

[12] Shahin MA, Jaksa MB, Maier HR. Artificial neural network based settlement prediction formula for shallow foundations on granular soils. Aust Geomech: J N Aust Geomech Soc. 2002 Sep;37(4):45–52.

[13] Shahin MA, Jaksa MB, Maier HR. Artificial neural network applications in geotechnical engineering. Aust Geomech. 2001 Mar;36(1):49–62.

[14] Recep AK. Estimation of the maximum bending moment of cantilever sheet pile walls by using multiple linear regression analysis. Mühendislik Bilimleri ve Tasarım Dergisi. 2022;10(1):247–56. doi: 10.21923/jesd.999619.

[15] Abdi Y, Garavand AT, Sahamieh RZ. Prediction of strength parameters of sedimentary rocks using artificial neural networks and regression analysis. Arab J Geosci. 2018 Oct;11:1. doi: 10.1007/s12517-018-3929-0.

[16] Tarawneh B, Imam R. Regression versus artificial neural networks: predicting pile setup from empirical data. KSCE J Civ Eng. 2014 May;18:1018–27. doi: 10.1007/s12205-014-0072-7.

[17] Mollahasani A, Alavi AH, Gandomi AH, Rashed A. Nonlinear neural-based modeling of soil cohesion intercept. KSCE J Civ Eng. 2011 May;15:831–40. doi: 10.1007/s12205-011-1154-4.

[18] Poulos HG, Davis EH. Pile foundation analysis and design. New York: Wiley; 1980 Jun.

[19] Whitaker T, Wilfrid R. 1 An investigation of the shaft and base resistances of large bored piles in London Clay. In Large bored piles. London: Thomas Telford Publishing; 1966. p. 7–49.

[20] Koelewijn AR, Maccabiani J. Three examples of using artificial neural networks in geotechnical engineering. In Proceedings of the 16th International Conference on Soil Mechanics and Geotechnical Engineering. Amsterdam: IOS Press; 2005. p. 1067–70. doi: 10.3233/978-1-61499-656-9-1067.

[21] Abidin DZ, Nurmaini S, Malik RF, Rasywir E, Pratama Y. RSSI data preparation for machine learning. In 2020 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS). IEEE; 2020 Nov. p. 284–9. doi: 10.1109/ICIMCIS51567.2020.9354273.

[22] Brownlee J. Data preparation for machine learning: data cleaning, feature selection, and data transforms in Python. In Machine Learning Mastery; 2020. p. 398

[23] Fatehnia M, Amirinia G. A review of genetic programming and artificial neural network applications in pile foundations. Int J Geo-Eng. 2018 Dec;9(1):2. doi: 10.1186/s40703-017-0067-6.

[24] Alcaide E. E-swish: Adjusting activations to different network depths. arXiv preprint arXiv:180107145; 2018 Jan. doi: 10.48550/arXiv.1801.07145.

[25] Ramachandran P, Zoph B, Le QV. Searching for activation functions. arXiv preprint arXiv:171005941; 2017 Oct. doi: 10.48550/arXiv.1710.05941.

[26] Clare L. 5 Concepts You Should Know About Gradient Descent and Cost Function. 2020 Accessed 7 May 2022. https://www.kdnuggets.com/2020/05/5-concepts-gradient-descent-cost-function.html.

[27] Fattah MY, Salim NM, Mohsin IM. Behavior of single pile in unsaturated clayey soils. Eng Technol J. 2014 Mar;32(3):763–87. doi: 10.30684/etj.32.3A.15.

[28] Ayasrah M, Fattah MY, Hamood MJ. Investigation on existing tunnel response to piles construction: A numerical study. Civ Eng J. 2023 Dec;9:202–16. doi: 10.28991/CEJ-SP2023-09-016.

Appendix

ANN Pseudocode:

Import standard library; NumPy, pandas, sklearn, TensorFlow, Keras, and matplotlib.

Read dataset of samples file has 13 parameters and 175 samples (features.csv)/pandas

Read separately the target file has 175 samples (target. CSV)/pandas

Convert the DataFrames features and targets to NumPy.arrays

Using the number of neurons in the first hidden layer = parameters No = 13

Using the number of neurons in the second hidden layer = parameters No/2 = 6

Normalization of features and targets

Randomly split the dataset to train 60%, test 40%, and validation 18% of trained data (/sklearn.

Save the data as x_train, y_train, x_test, and y_test.

Customization of the external activation function (E-swish function, $ß$ = 1.5) for all hidden layers outcomes.

Update of custom_objects for the Keras model.

Build an ANN model using Keras. sequential

Using Mean Squared Logarithmic Error (MSLE), loss function

Compile with Adam optimizer and learning rate = 0.01

History fitting X_train and Y-train and epoch = 100

Prediction model

Save the weights and biases for all layers