BILINGUAL PUBLISHING GROUP

Journal of Electronic & Information Systems

https://journals.bilpubgroup.com/index.php/jeis

ARTICLE

Ground Surface Deformation Prediction Using Machine Learning Approaches

Miller Mark [1*], Fang Yong [1], Kharitonov Sergey [2], Akulich Vladimir [3], Noskov Ivan [1]

[1] Key Laboratory of Transportation Tunnel Engineering of Ministry of Education, School of Civil Engineering, Southwest Jiaotong University, Chengdu 610031, China

[2] Department of Bridges and Tunnels, School of Railway Track, Structure and Construction, Russian University of Transport (RUT MIIT), Moscow 127994, Russia

[3] Department of Theoretical Mechanics, School of Railway Track, Structure and Construction, Russian University of Transport (RUT MIIT), Moscow 127994, Russia

ABSTRACT

This study aims to investigate the use of machine learning algorithms to predict the settlements of the ground surface triggered by tunneling using a shielding method. First, a 2D tunnel calculation scheme was proposed for nonlinear construction stage analysis using the "contraction" load, which can be used to simulate the soil volume loss. Further, this model was verified by comparing the solution with the analytical method and numerical simulation, which uses standard modeling approaches, including in the spatial formulation. Then, after briefly describing the main theoretical substantiation of machine learning techniques, the 2D scheme was used to create the dataset. Finally, the dataset was processed by the machine learning algorithms: linear regression, decision tree, random forests, polynomial regression, ridge regression and neural network, which showed the best forecasting ability (R^2 = 0.985; RMSE = 0.000986). The results indicate that machine learning can provide a robust approach for predicting ground settlements, mitigating risks associated with tunneling operations. Additionally, this research highlights the potential of integrating advanced computational methods with traditional engineering analyses, enhancing the accuracy and efficiency of settlement prediction. Future work will explore

*CORRESPONDING AUTHOR:

Miller Mark, Key Laboratory of Transportation Tunnel Engineering of Ministry of Education, School of Civil Engineering, Southwest Jiaotong University, Chengdu 610031, China; Email: millermark.swjtu@yandex.ru

ARTICLE INFO

Received: 24 September 2024 | Revised: 8 October 2024 | Accepted: 13 October 2024 | Published Online: 18 October 2024
DOI: https://doi.org/10.30564/jeis.v6i2.8201

CITATION

Mark, M., Yong, F., Sergey, K., et al., 2025. Ground Surface Deformation Prediction Using Machine Learning Approaches. Journal of Electronic & Information Systems. 6(2): 38–48. DOI: https://doi.org/10.30564/jeis.v6i2.8201

the applicability of these algorithms to different soil and geological conditions, aiming to further improve predictive models in geotechnical engineering. By establishing a strong correlation between simulated parameters and machine-learning outcomes, this study opens avenues for more intelligent and adaptive tunneling practices.

Keywords: Subway; Tunnel; Forecasting Ground Surface Settlement; Machine Learning; Artificial Neural Network; Decision Tree

1. Introduction

Nowadays, machine learning algorithms have been widely used in various aspects of human activity, continuing to develop and improve. Within the framework of ground surface settlement prediction, the ability of machine learning to solve a regression problem is used, in which an algorithm based on an initial dataset predicts the value. Moreover, machine learning methods are adapted for various fields of civil engineering, such as prediction of bridge deck deterioration[1], seismic damage prediction[2], tunnel crack identification[3, 4], etc.

Many researchers are engaged in predicting the deformations of the surface when tunneling with the help of artificial intelligence[5, 6]. While the vast majority of research focuses on specific study cases, this article offers a generalized approach to creating datasets from different projects with variable parameters, such as tunnel depth, soil characteristics and soil volume loss.

2. Problem Statement

To use the machine learning method for predicting the ground surface settlements it is necessary to have a dataset for training models. Previously, obtaining such a dataset was associated with a large expenditure of time and computational resources to create and calculate a finite element model, but the tool "Contraction" in Midas GTS NX software allows one to set shrinking of the tunnel lining. In general, this approach is a convention, since it is impossible to assess the stress-strain state of the tunnel lining in such conditions, however this tool can be used in one specific engineering task: assessing the impact of the construction of a new tunnel on the surface. During the construction of a tunnel by the shield method, due to the gap between the outer shell of the shield and the lining, a soil volume loss occurs, which has an influence on the deformation of the ground surface. Using the simplest geometric transformations, it is possible to express the soil volume loss through the shrinking of the tunnel lining.

The numerical simulation is a nonlinear construction stage analysis of a planar calculation scheme. The lining material is assumed to be infinitely linearly elastic. The physical and mechanical properties of the lining correspond to the properties of concrete: modulus of elasticity $E = 3.8 \times 10^4$ MPa, Poisson's ratio $\mu = 0.2$, density $\rho = 24.5$ kN/m^3. The shape of the lining is accepted according to the standard design: diameter –6.0 m; thickness –0.3 m. The distance from the ground surface to the center of the tunnel z varies from 8 to 23 meters (**Figure 1**). The amount of contraction varies from 0.1% to 2.7% (which corresponds to about 5.3% of soil loss). The soil array is described by the popular Mohr-Coulomb model with varying parameters:

$$2.5 \leq E \leq 50 \text{ MPa}; \; 0 \leq c \leq 38 \text{ kPa}; \; 7 \leq \varphi \leq 43°;$$
$$0.3 \leq \mu \leq 0.42$$

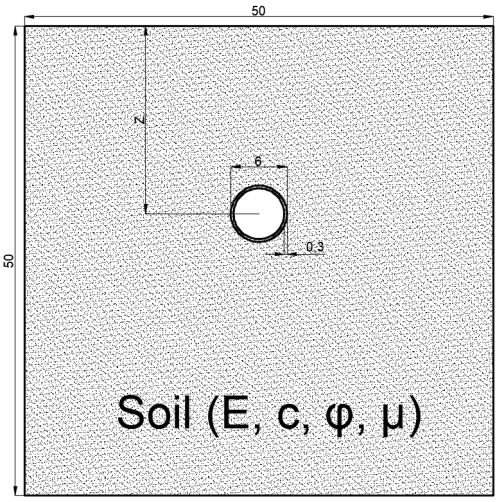


Figure 1. Accepted calculation scheme used for dataset producing.

Before performing the numerical simulations directly, the verification of the method was carried out by solving a test task, which is described in the following paragraph.

3. Test Task

At first, the problem was solved analytically using the Park solution[7]. The displacements in polar coordinate system are obtained as follows:

$$u_r = -\frac{1.5}{E}\left(\frac{a_0}{r} + \frac{\gamma a^2}{2}\ln r sin\theta\right) \quad (1)$$

$$u_\theta = -\frac{1.5}{E}\frac{\gamma a^2}{2}(1 + \ln r)cos\theta \quad (2)$$

And the surface settlements:

$$u_z = u_r sin\theta - u_\theta cos\theta = -\frac{1.5}{E} \left[\frac{a_0}{r}sin\theta + \frac{\gamma a^2}{2}(\ln r\left(sin^2\theta - cos^2\theta\right) - cos^2\theta)\right] \quad (3)$$

Where E is Young's modulus, r and θ are the polar coordinates (**Figure 2**), γ is the unit weight, a is the tunnel radius, a_0 is the coefficient depending on boundary conditions.

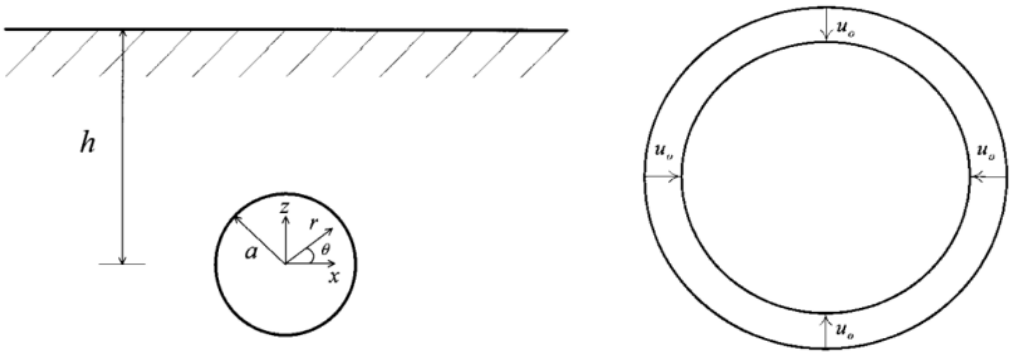


Figure 2. Coordinate systems (**left**) and boundary conditions of prescribed displacements (**right**).

The following boundary condition of the prescribed displacements is considered around the tunnel:

$$u_r\,(r = a) = -u_0 \quad (4)$$

The value $u_0 = 0.5g$ and g = gap parameter estimated by following the procedure suggested by Lee[8].

Numerical simulation is performed in a planar and spatial formulation (**Figure 3**). The two-dimensional problem is an object of interest, since this model is used to create a dataset, as mentioned earlier. The three-dimensional problem is a multi-stage nonlinear analysis, in which the soil is sequentially extracted and the tunnel lining is installed. Next, the "contraction" load and friction are added to the spatial scheme. The friction between the shell element of the tunnel lining and the solid element of the soil is represented as a plane interface element[9].

The tunnel is accepted with a diameter of 5 m and a thickness of 0.25 m, the distance from the surface to the tunnel center is 20 m, the lining material is adopted with the characteristics of concrete: $E = 3.8 \times 10^4$ MPa, μ = 0.2, ρ = 24.5 kN/m^3, the soil is assumed as sand: $E = 30$ MPa, $c = 10$ kPa, φ = 25°, μ = 0.3, ρ = 20 kN/m^3. The results are shown in **Figure 4**.

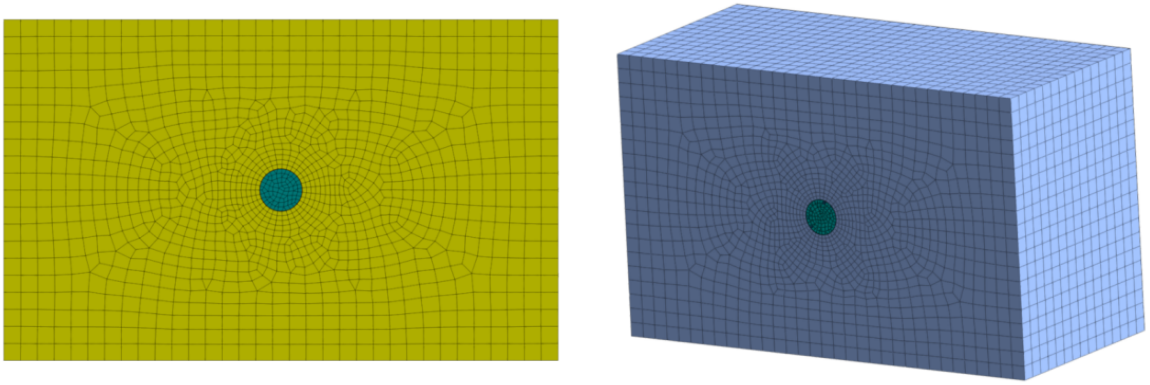


Figure 3. 2D (**left**) and 3D (**right**) calculation schemes.

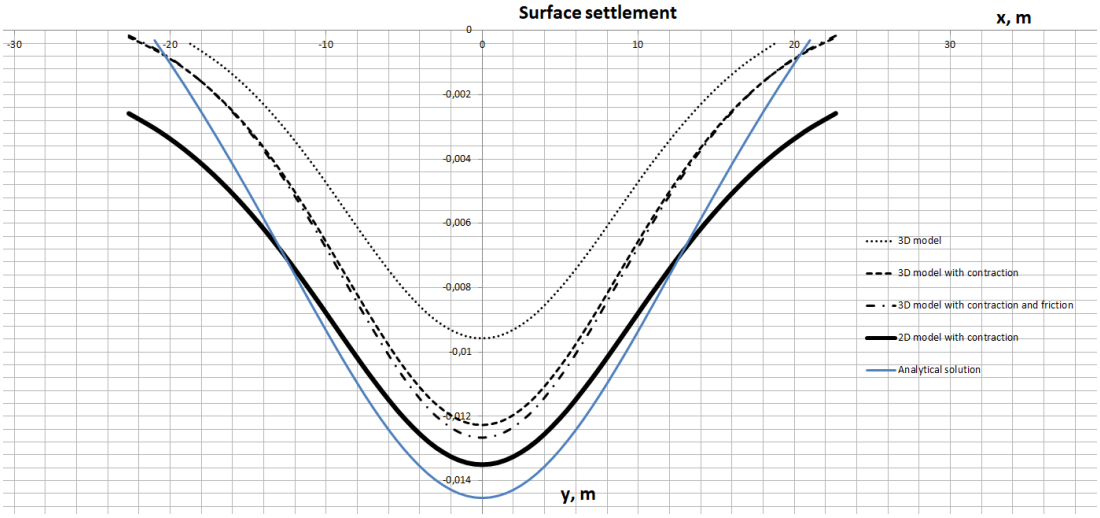


Figure 4. Surface settlement values obtained by analytical solution and numerical simulation.

The spatial calculation scheme with a construction stage analysis only under the influence of gravity gives the smallest value of the settlement (0.00955 m). It is noteworthy that when the "contraction" load is added, the settlement increases to 0.0125 m. The case is also calculated with additional consideration of the friction in the 3D scheme, which increases the settlement to 0.0129 m. Due to the complexity of accounting for the friction (the properties of interface elements should be recalculated each time depending on the parameters of the surrounding soil mass and the elements themselves complicate achieving the desired convergence of the solution) and its negligible influence (3.2%), it was decided not to take the friction into account when generating the dataset to save time and computing resources. The target 2D model itself, which is verified in this test task, demonstrates the results of the settlement of 0.0135 m. The maximum settlement value is obtained using an analytical solution (0.0145 m).

Thus, when studying the issues of assessing the impact of tunnel construction on the ground surface settlement, it is permissible to use the "contraction" load. The flat calculation scheme shows reliable results, the model can be considered verified.

4. Machine Learning

Machine learning[10] is a branch of the science of artificial intelligence that studies methods for constructing algorithms capable of learning. It is based on the idea that a system of such algorithms can learn to identify patterns and make decisions with minimal human involvement. Machine learning is at the intersection of mathematical statistics, optimization methods and classical mathematical disciplines, but it also has its unique field of research related to the problems of computational efficiency and retraining. Many methods have been developed as an alternative to classical statistical approaches and are closely related to information extraction and data mining.

4.1. Linear Models

4.1.1. Ordinary Least Squares

Ordinary Least Squares (OLS) linear regression is a statistical method used for modeling the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data. The goal is to find the line of best fit, which minimizes the sum of squared differences between the observed response and the response predicted by the linear model. The method provides an estimate of the coefficients of the linear equation, which can be used to make predictions about the response variable based on new observations of the independent variables.

4.1.2. Ridge Regression

Ridge Regression is a type of regularized linear regression algorithm that aims to minimize the residual sum of squares between the predicted response and the true response by adding a penalty term to the loss function[11]:

$$P^{Ridge}(\beta) = \lambda \sum_{j=1}^{p} \beta_j^2 \quad (5)$$

$$L^{Ridge}(\beta) = \|Y - X\beta\|^2 + \lambda\beta^T\beta \quad (6)$$

This penalty term, called "*L2* regularization", helps to reduce the model complexity and avoid overfitting. The regularization term is the sum of the squares of the coefficients, multiplied by a hyperparameter lambda, which determines the strength of the regularization. Larger values of lambda result in a more restricted model with smaller coefficients, while smaller values result in a less restricted model with larger coefficients. The optimal value of lambda is usually determined by cross-validation. Ridge regression is well-suited for cases where the number of predictors is large compared to the number of observations, or where some predictors are highly correlated.

4.1.3. Polynomial Regression

Polynomial Regression is a form of regression analysis in which the relationship between the independent variable *x* and the dependent variable *y* is modeled as an *n*th degree polynomial. In polynomial regression, the independent variable is raised to a power to create a new set of predictors, which can model non-linear relationships between the dependent and independent variables. The model is trained using a training dataset, and the coefficients of the polynomial are estimated using optimization techniques such as gradient descent. The goal is to find the polynomial that best fits the data, as measured by an appropriate error metric. Once the model is trained, it can be used to make predictions for new data points.

4.2. Artificial Neural Network

Artificial neural network (ANN) is formed by several neurons as an information processing unit serving as the basis for the performing of a function in accordance with its task[12]. A neuron is an element that calculates an output signal using a particular rule from a set of input signals. It consists of weights inputs, a function of summation, a function of activation and output (**Figure 5**). Neurons can be connected to each other in different ways, but the essence of the neural network always remains the same — transmitting information ahead.

Thus, the input data is sent to the hidden layers for computing. Finally, the last hidden layer sends the processed information to the output layer, and receives the results. In this study, a fully connected neural network is used, in which each neuron of one layer is sequentially connected to each neuron of the subsequent layer, including the input, hidden and output layers (**Figure 6**).

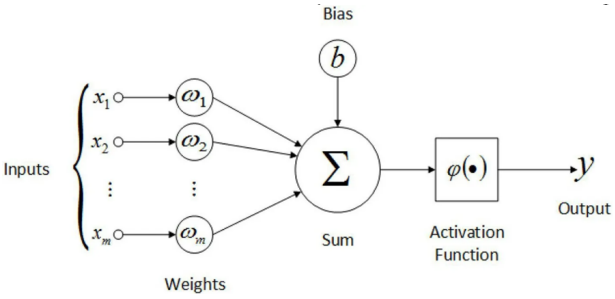


Figure 5. Simplified model of an artificial neuron.

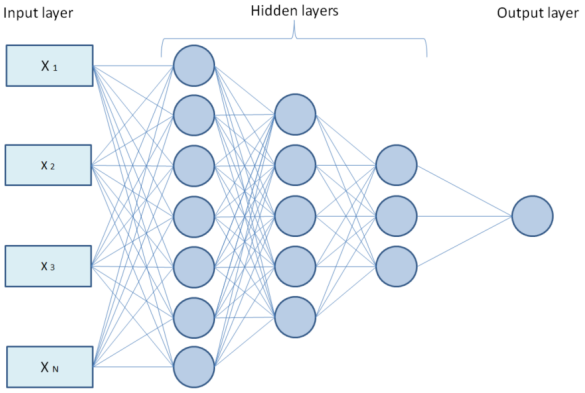


Figure 6. Schematic of an artificial neural network.

Different weights describe the different influence of neighboring neurons on a particular one. These parameters are configured by the network itself during training. The weighted sum of the input data is transmitted to the hidden neurons, where it is transformed using the activation function. The process of obtaining output data is described by the equation:

$$Y_k^{n+1} = f\left(\sum\nolimits_{i=1}^{N} X_i^n w_{ki}^n + b_i^n\right) \quad (7)$$

Where Y_k^{n+1} is output of unit *k* in the *n*th layer, f is the function of activation, X_i^n is the input vector, w_{ki}^n is a weight vector, b_i^n is the bias weight.

The initial values of the weights are often set randomly, and the training of the neural network is the selection of weights — backpropagation algorithm.

Application of the network training rules for backpropagation consists of two stages: feedforward and backward propagation. A set of training examples called training set

is given on the network. This training set is represented by a feature vector called the associated input vector with an output that is the target of the training. In other words, the training set consists of an input vector and a target output vector. Exodus from the network is an actual output vector. Next, a comparison is made between the actual output produced and the target output by reducing the two outputs. The result of the reduction is an error. Errors are used to make changes to each weight by re-propagating it. Any weight changes that occur can reduce errors. Cycle weight changes (epochs) are carried out in each training set so that the 50 stop is reached, when the set number of epochs is reached or when a set threshold value is passed. The backpropagation network training algorithm consists of 3 stages:

(1) The feedforward stage. The input layer is first calculated by summing the weight and bias values up to the output layer using a predetermined activation function.
(2) The stage of feedback (backpropagation). The difference between network output with the desired target is calculated, which is then referred to as an error. Next is the back-propagation phase, where the error factor is propagated backward, starting from the corresponding line directly with the units in the output layer.
(3) The stage of updating the weights and biases. The last phase is modifying the weights to reduce occurred errors[13].

4.3. Decision Tree

The decision tree is an effective tool for data mining and predictive analytics. It helps in solving classification and regression problems. The decision tree is a hierarchical tree structure consisting of a "If ... then ..." rule. Due to useusing the training set, the rules are generated automatically during the training process. The rules are generated by generalizing a set of individual observations (training examples) describing the subject area. Therefore, they are called inductive rules, and the learning process itself is called the induction of decision trees. In the training set, a target value should be set for the examples, since decision trees are models created based on supervised learning. Two types of trees are distinguished by the type of variable: classification tree, when the target variable is discrete, and regression one, when the target variable is continuous.

The root node, or the decision node, represents an option that will occur in splitting all records into two or more mutually exclusive subsets. Internal nodes, or random nodes, are one of the possible options available at this stage of the tree structure; the upper edge of the node is connected to its parent node, and the lower edge is connected to its child nodes or leaf nodes. Leaf nodes, or end nodes, are the final result of a combination of decisions or events (**Figure 7**).

Before compiling the model, the most significant input variables shall be identified first, and then based on the status of these variables the records at the root node and at subsequent internal nodes shall be divided into two or more categories or "bins". Characteristics entropy, Gini index, classification error, information gain, gain ratio and twoing criteria[14] are related to the degree of "purity" of the resultant child nodes (i.e., the proportion with the target condition) and used to select between different potential input variables. This splitting procedure continues until pre-determined homogeneity or stopping criteria are met. In most cases, not all potential input variables will be used to build the decision tree model and in some cases a specific input variable may be used multiple times at different levels of the decision tree[15].

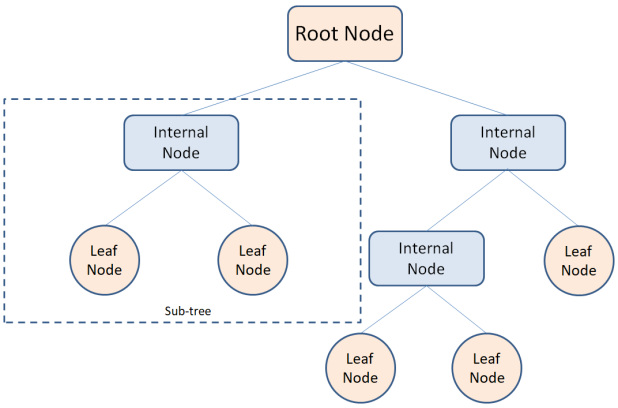


Figure 7. Schematic of a simple decision tree.

4.3.1. Classification and Regression Tree (CART)

The CART (Classification and Regression Tree) algorithm recursively divides the original dataset into subsets that become more and more homogeneous with respect to certain features, resulting in a tree-like hierarchical structure[16]. The division is carried out on the basis of traditional logical rules in the form of IF (A) THEN (B), where A is some logical condition, and B is the procedure for dividing

a subset into two parts, for one of which condition A is true, and for the other it is false.

At the first iteration, the root node of the tree is associated with the most optimal conditional judgment, and the entire set of objects is divided into two groups. Two branches can also branch off from each subsequent parent node to the descendant nodes, which in turn are associated with the boundary values of other most suitable variables and determine the rules for further splitting (splitting criterion). The final nodes of the tree are the "leaves" corresponding to the solutions found and combining all the objects of the training sample divided into groups.

The described process refers to the so-called "greedy" algorithms that strive, regardless of anything, to build the most "bushy" tree (also "deep tree"). Naturally, the more extensive and bushier the tree, the better the results of its testing will be on the training sample, but not as successful on the test sample. Therefore, the constructed model must also be optimal in size, i.e., contain information that improves the quality of recognition, and ignore the information that does not improve it. To ensure this, it is common to "prune" the tree (tree pruning) – to cut off branches where this procedure does not lead to a serious increase in errors.

It is impossible to find an objective internal criterion that leads to a good compromise between error-free and compact, thus the standard mechanism for optimizing trees is based on cross-validation[17]. To do this, the training sample is divided, for example, into 10 equal parts: 9 parts are used to build a tree, and the remaining part plays the role of verification aggregate. After repeating this procedure many times, the tree that showed the best result during cross-validation is selected from a certain set of candidate trees that have a practically acceptable range of model quality criteria.

4.3.2. Random Forests (RF)

Random forests is a method invented after CART by Leo Breiman, which is based on the use of a committee (ensemble) of decision trees[18]. The essence of the algorithm is that at each iteration a random sample of variables is made, after which, on this new sample, the construction of a decision tree begins. At the same time, "bagging" is performed — a sample of random two-thirds of observations for training, and the remaining third is used to evaluate the result. This operation is performed hundreds or thousands of times. The resulting model will be the result of a "vote" of a set of trees obtained during modeling.

4.4. Statistical Accuracy Measurement

When using forecasting machine learning models, there is always some degree of uncertainty. The accuracy and correctness of the prediction results are characterized by the magnitude of the prediction error, which shows the difference between the actually measured value and the predicted one. There are five main indicators to evaluate the accuracy and forecasting power: the predictive coefficient of determination R^2, the mean absolute error (MAE), the mean absolute percentage error (MAPE), the mean square error (MSE), the root mean square error (RMSE).

$$R^2(y,\widehat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i-\widehat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^2}, \quad where\ \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{8}$$

$$MAE(y,\widehat{y}) = \frac{1}{n}\sum_{i=1}^{n}|y_i-\widehat{y}_i| \tag{9}$$

$$MAPE(y,\widehat{y}) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\widehat{y}_i}{y_i}\right| \tag{10}$$

$$MSE(y,\widehat{y}) = \frac{1}{n}\sum_{i=1}^{n}(y_i-\widehat{y}_i)^2 \tag{11}$$

$$RMSE(y,\widehat{y}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\widehat{y}_i)^2} \tag{12}$$

where $y, \widehat{y}$ — actual and predicted value respectively.

In this research, RMSE and R^2 score are used to evaluate the performance of machine learning algorithms.

4.5. Dataset

The dataset is a table of 400 rows, each of which contains data on a separate calculation case, and 7 columns (soil parameters: Young's modulus, cohesion, frictional angle, Poisson's ratio; depth of location of the central axis of the tunnel; the amount of lining shrinking through which the soil volume lost is expressed; surface settlement, which is the target value for forecasting). **Figure 8** shows a correlation matrix of features, from which it can be seen that the features with the highest influence on the settlement are contraction (0.74) and the distance from the surface to the center of the tunnel (0.29).

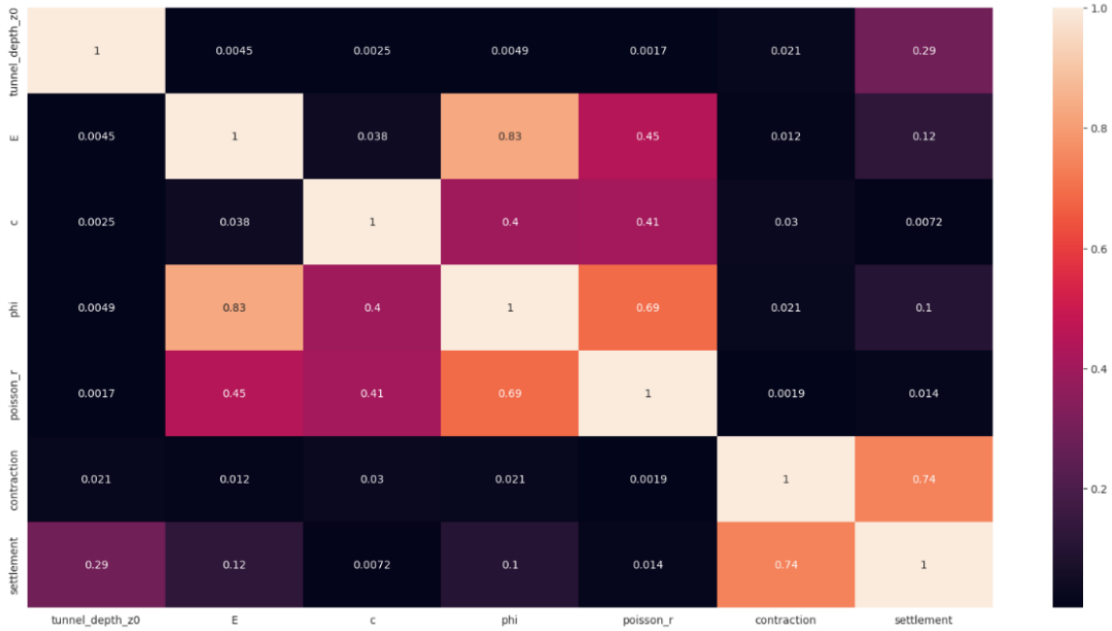


Figure 8. Correlation matrix of the features.

4.6. Results

To determine the reliability of the proposed machine learning solutions, solving algorithms are trained with a training set. The entire volume of data is randomly divided in training (60%), validation (20%) and test (20%) sets.

Figure 9 shows the results of comparing calculated settlement values and predicted values by the algorithms. Each graph contains dot diagrams, which are plotted relative to the line $y = x$ and show a correlation between predictions of the models and settlements obtained by the numerical simulation.

In **Figure 10**, the models are sorted in descending order by the magnitude of the R^2 score for the test set. The neural network model has the best predictive ability with the value $R^2 = 0.985$; worst of all, as expected, the linear regression model copes with the prediction with the value of $R^2 = 0.879$.

In **Figure 11**, the models are sorted by the RMSE value from the largest value (Linear regression, RMSE = 0.00278) to the smallest one (Neural network, RMSE = 0.000986).

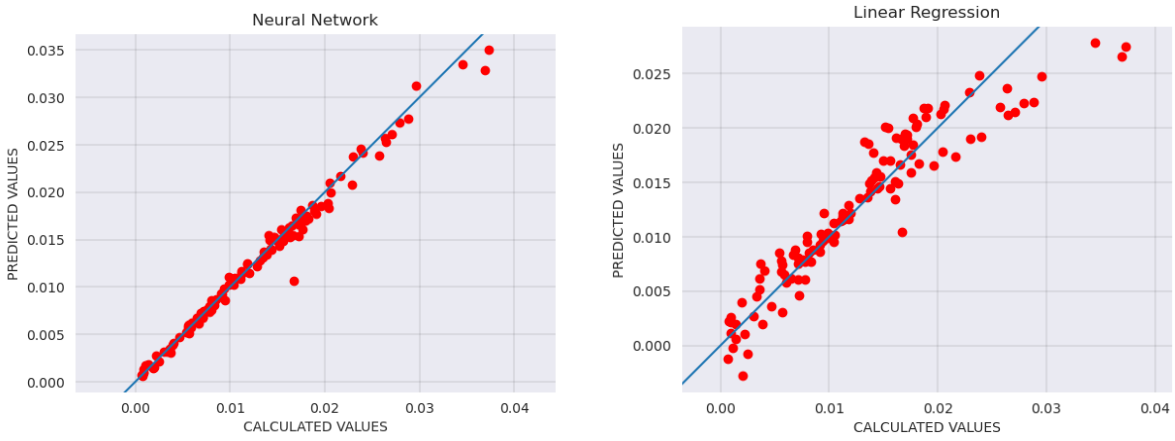
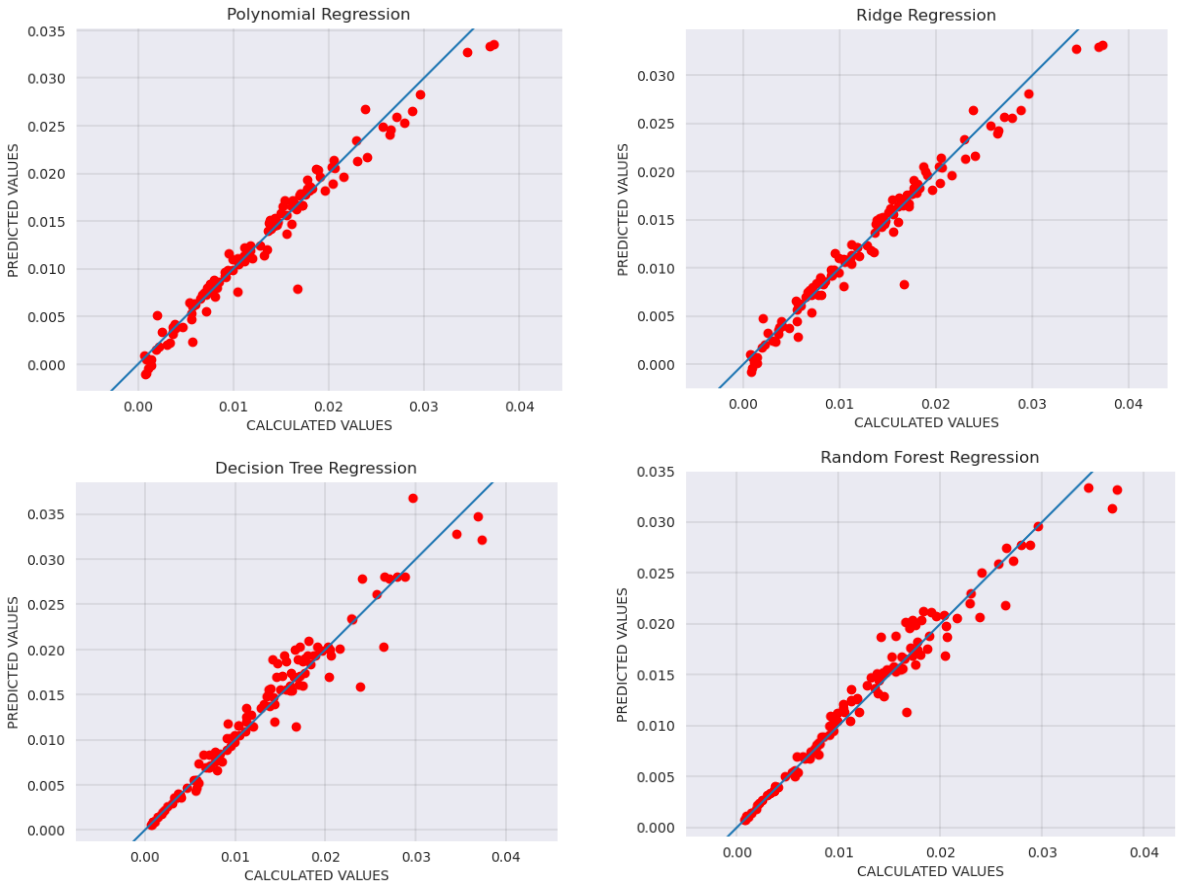


Figure 9. *Cont.*



Model	RMSE	R2_Score(test)
Neural network	0.000986	0.984799
Linear Regression	0.002780	0.879168
Polynomial Regression (2nd)	0.001471	0.966175
Ridge Regression	0.001425	0.968274
Decision Tree	0.001878	0.944875
Random Forest	0.001501	0.964773

Figure 9. Results of the forecasting models, the values of RMSE and R^2 scores for each model.

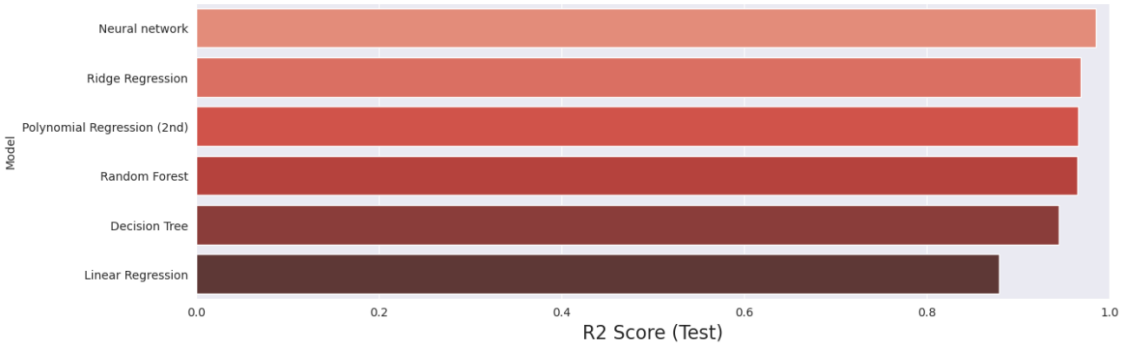


Figure 10. Gradation of the models by value R^2 Score.

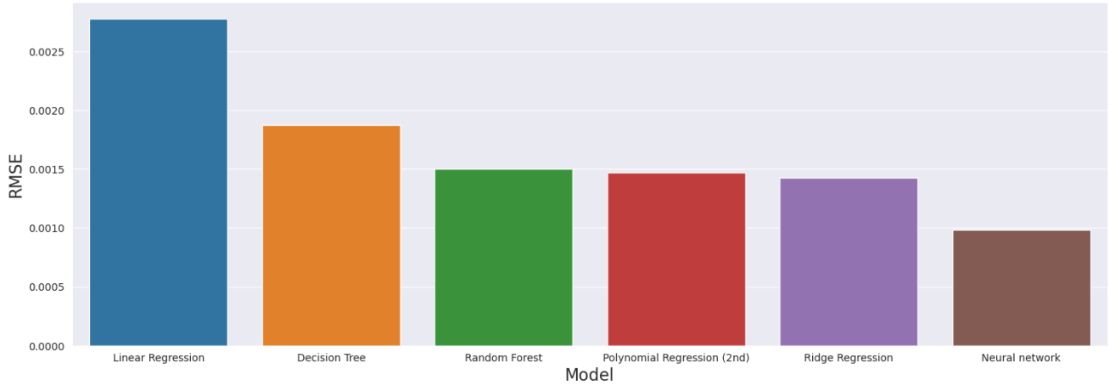


Figure 11. Gradation of the models by value RMSE.

5. Conclusions and Future Prospects

This study shows that machine learning techniques can be used to accurately predict ground surface settlements caused by tunneling, thereby improving tunnel excavation efficiency.

The two-dimensional calculation scheme using the "contraction" loading is proposed; verification of the solution of this approach is carried out by comparing it with the spatial formulation of the problem and the analytical method. A theoretical description of machine learning algorithms is given. Then the data is processed and prepared for machine learning analysis. Finally, several machine learning algorithms are applied to the data, including linear regression, decision tree, random forest, polynomial regression, ridge regression and neural network to predict the settlements of ground surface. The results show that the neural network outperformed the other algorithms in terms of accuracy, achieving an R-squared value of 0.985.

Overall, the study highlights the potential of machine learning for improving the efficiency and accuracy of tunnel excavation. Authors hope that presented findings will encourage further research in this area and help to advance the field of tunneling engineering.

This article is intended as an initial study. In the foreseeable future, it is planned to search for data on settlements of the ground surface from real objects and construction sites. The model for the numerical simulation will be complicated for more sensitive analysis: the use of two metro tunnels instead of one, which will simulate a real subway line; several layers of soil of different properties will be taken into account; it is assumed transition from the Mohr Coulomb Model to the Hardening Soil Model [19], which more accurately describes the behavior of soils.

Author Contributions

Conceptualization, M.M. and F.Y.; methodology, M.M., F.Y., K.S. and A.V.; software, M.M., K.S. and A.V.; validation, M.M., K.S. and A.V.; formal analysis, M.M., F.Y.; investigation, M.M., N.I.; resources, F.Y.; data curation, F.Y.; writing—original draft preparation, M.M.; writing—review and editing, A.V.; visualization, N.I.; supervision, F.Y.; project administration, F.Y.; funding acquisition, F.Y. All authors have read and agreed to the published version of the manuscript.

Funding

This work was financially supported by the National Natural Science Foundation of China [52078428].

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data is available on reasonable request to the corresponding author.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Rashidi Nasab, A., Elzarka, H., 2023. Optimizing machine learning algorithms for improving prediction of bridge deck deterioration: A case study of Ohio bridges. Buildings. 13(6), 1517. DOI: https://doi.org/10.3390/buildings13061517

[2] Bhatta, S., Dang, J., 2023. Seismic damage prediction of RC buildings using machine learning. Earthquake Engineering & Structural Dynamics. 52(11), 3504–3527. DOI: https://doi.org/10.1002/eqe.3907

[3] Dang, L.M., Wang, H., Li, Y., et al., 2022. Automatic tunnel lining crack evaluation and measurement using deep learning. Tunnelling and Underground Space Technology. 124, 104472. DOI: https://doi.org/10.1016/j.tust.2022.104472

[4] Liao, J., Yue, Y., Zhang, D., et al., 2022. Automatic tunnel crack inspection using an efficient mobile imaging module and a lightweight CNN. IEEE Transactions on Intelligent Transportation Systems. 23(9), 15190–15203. DOI: https://doi.org/10.1109/TITS.2021.3138428

[5] Li, C., Li, J., Shi, Z., et al., 2022. Prediction of surface settlement induced by large-diameter shield tunneling based on machine-learning algorithms. Geofluids. 2022(1), 4174768. DOI: https://doi.org/10.1155/2022/4174768

[6] Liu, L., Zhou, W., Gutierrez, M., 2023. Physics-informed ensemble machine learning framework for improved prediction of tunneling-induced short- and long-term ground settlement. Sustainability. 15(14), 11074. DOI: https://doi.org/10.3390/su151411074

[7] Park, K.H., 2004. Elastic solution for tunneling-induced ground movements in clays. International Journal of Geomechanics. 4(4), 310–318. DOI: https://doi.org/10.1061/(ASCE)1532-3641(2004)4:4(310)

[8] Lee, K.M., Rowe, R.K., Lo, K.Y., 1992. Subsidence owing to tunnelling. I. Estimating the gap parameter. Canadian Geotechnical Journal. 29(6), 929–940. DOI: https://doi.org/10.1139/t92-104

[9] Miller, M.R., Titov, E.Y., Kharitonov, S.S., et al., 2022. The stress-strain state of the tunnel lining that crosses the fault zone of soil blocks during an earthquake. Communications-Scientific Letters of the University of Zilina. 24(1), D9–D22.

[10] Miller, M., Yong, F., Hu, L., et al., 2023. Prediction of subway vibration values on the ground level using machine learning. Geotechnical and Geological Engineering. 41(6), 3753–3766. DOI: https://doi.org/10.1007/s10706-023-02486-6

[11] McNeish D. M., 2015. Using Lasso for predictor selection and to assuage overfitting: A method long overlooked in behavioral sciences. Multivariate Behavioral Research. 50(5), 471–484. DOI: https://doi.org/10.1080/00273171.2015.1036965

[12] Fausett, L.V., 1993. Fundamentals of neural networks: Architectures, algorithms, and applications. Pearson Education India: New Delhi, India. p. 480.

[13] Afandi, A., Lusi, N., Catrawedarma, I.G.N.B., et al., 2022. Prediction of temperature in 2 meters temperature probe survey in Blawan geothermal field using artificial neural network (ANN) method. Case Studies in Thermal Engineering. 38, 102309. DOI: https://doi.org/10.1016/j.csite.2022.102309

[14] Patel, N., Upadhyay, S., 2012. Study of various decision tree pruning methods with their empirical comparison in WEKA. International Journal of Computer Applications. 60(12), 20–25. DOI: https://doi.org/10.5120/9744-4304

[15] Song, Y.Y., Ying, L.U., 2015. Decision tree methods: Applications for classification and prediction. Shanghai Archives of Psychiatry. 27(2), 130. DOI: https://doi.org/10.11919/j.issn.1002-0829.215044

[16] Breiman, L., Friedman, J., Olshen, R.A., et al., 1984. Classification and Regression Trees, 1st ed. Chapman and Hall/CRC: New York, US. DOI: https://doi.org/10.1201/9781315139470

[17] Loh, W.Y., Shih, Y.S., 1997. Split selection methods for classification trees. Statistica Sinica. 7, 815–840.

[18] Breiman, L., 2001. Random forests. Machine Learning. 45(1), 5–32. DOI: https://doi.org/10.1023/A:1010933404324

[19] Cocco, L.J., Ruiz, M.E., 2018. Numerical implementation of hardening soil model. In: Cardoso, A., Borges, J., Costa, P., et al. (eds.). Numerical Methods in Geotechnical Engineering IX, Volume 1. CRC Press: London, UK. pp. 195–203.