Received: 1 July 2022 | Revised: 5 August 2022 | Accepted: 12 August 2022 | Published online: 15 August 2022

RESEARCH ARTICLE

Journal of Computational and Cognitive Engineering
2024, Vol. 3(2) 166–175
DOI: 10.47852/bonviewJCCE2202307

BON VIEW PUBLISHING

Utilizing Artificial Intelligence and Finite Element Method to Simulate the Effects of New Tunnels on Existing Tunnel Deformation

Abolfazl Baghbani[1],*, Hasan Baghbani[2], Mohamad Mahdi Shalchiyan[3] and Katayoon Kiany[4]

[1]*School of Engineering, Federation University, Australia*

[2]*School of Engineering, Ferdowsi University, Iran*

[3]*School of Engineering, Guilan University, Iran*

[4]*Titi Company, Iran*

Abstract: Buildings and infrastructure should be constructed while maintaining the safety of the existing infrastructure. Since tunnels are an essential component of urban infrastructure, building new tunnels next to existing ones may have unintended consequences. This study aims to examine the effects of building a new tunnel next to an existing tunnel under different conditions. Two-dimensional models have been developed using the finite element method (FEM) for the existing tunnel, with a diameter of 5 meters, and for the new tunnel, with a diameter that differs from the existing tunnel. Then, the effects of two factors, namely the distance between the two tunnels and the diameter of the new tunnel, were examined on the horizontal, vertical, and total deformation of the soil and the existing tunnel. For the first time, this study attempts to predict the effect of new tunnels on existing tunnels using artificial intelligence (AI) methods. Due to the importance of tunnels and the increasing number of tunnels being constructed in urban areas, this issue will be of great interest. For analyzing the feasibility of using mathematical methods to predict tunnel deformation, the multiple linear regression (MLR) method and an AI technique, namely classification and regression random forests (CRRFs), were used to utilize the generated database. Analyzing FEM results represented that by increasing the diameter of the new tunnel from 3 to 5, horizontal and vertical displacement of the existing tunnel increased by approximately 5 and 10 times, respectively. Further, by reducing the distance between the new tunnel and the existing tunnel from 11 meters to 6 meters, the intensity of horizontal and vertical deformation of the existing tunnel increased by about 2 and 3 times, respectively. Moreover, the results of mathematical models demonstrated that the CRRF method was more accurate than the MLR method, with R of 0.94 and mean absolute error of 2.89 for the testing database, which indicated its proper performance.

Keywords: tunneling, finite element method, deformation, classification and regression random forest, multiple linear regression, artificial intelligence

1. Introduction

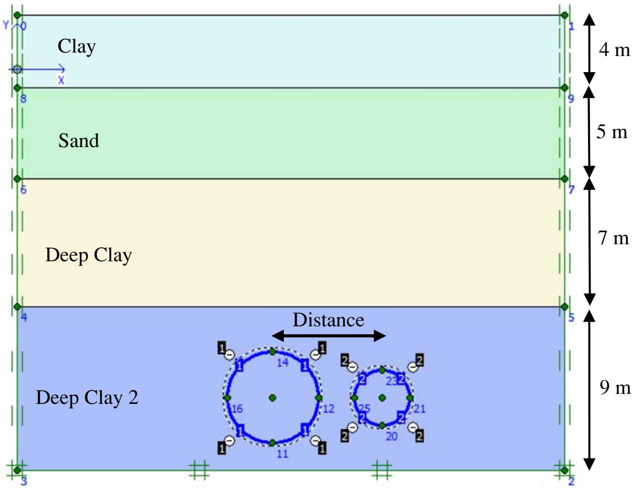
The construction of tunnels for urban infrastructure is rising in urban areas. The construction of these structures continues to increase, and its effects must be studied and controlled. In general, when a new tunnel is constructed, the existing tunnels must be maintained and should be able to continue to function as expected. Therefore, a number of issues and regulations need to be established in order to determine the permissible deformations of new tunnels [1–3].

The numerical analysis method has been used in several studies to investigate multi-tunnel excavation [4, 5]. Models such as nonlinear elastic models [6], Mohr–Coulomb models [7–9], modified Cam Clay models [6, 10, 11], and soil hardening models [12–14] have been used to analyze different problems such as soil and tunnel deformation [5]. There have been a number of field studies conducted to investigate tunnel–tunnel interactions [2, 5, 15–18]. Cooper et al. [5] showed that the successive construction of three new tunnels has increased the deformation of the first tunnel and caused asymmetry in the ground surface settlement troughs over the long term.

Numerical analysis can be used to understand better the intersection of tunnel problems and tunnel intersection problems. Several papers have addressed tunnel–tunnel interaction numerically and for parallel tunnels [15, 19, 20]. Generally, these studies examined the effects of distance and relative position of tunnels. It was found by Addenbrooke et al. [21] that tunnels can

***Corresponding author:** Abolfazl Baghbani, School of Engineering, Federation University, Australia. Email: n.baghbani@federation.edu.au.

Figure 1
Soil profile and general geometry



affect each other if the distance between them is less than seven times their diameter.

In spite of the research conducted on this topic, the literature did not provide a systematic investigation into the effect of new tunnels on the existing tunnels. Studying the deformation of the existing tunnel as a result of the new tunnel was the objective of this study. Furthermore, although artificial intelligence (AI) methods had shown positive performance in geotechnical engineering when it came to predicting various parameters [22–25], no study has yet been carried out that deals with the effects of tunnels on each other. Various studies used AI in the field of tunneling [26–28]. For instance, Shi et al. [27] applied the support vector machine (SVM) method to predict the rock deformation around the Panlongshan tunnel on the Qinglan highway line in China. Based on the results of this study, it can be concluded that the proposed method can be used effectively to predict rock deformations in the surrounding region [27].

In this study, AI is used for the first time to predict the impact of digging new tunnels on existing tunnels. For this reason, using two-dimensional (2D) modeling, new tunnels were modeled at different distances and with varying diameters. Following this, the deformation of the soils and existing tunnel due to the excavation of the new tunnel was examined in both horizontal and vertical directions. In order to predict the horizontal and vertical deformation of the existing tunnel due to the new tunnel, multiple linear regression (MLR) and classification and regression random forest (CRRF) methods were applied following the acquisition of the database.

2. Finite Element Method Modeling

2.1. Geometry

This research utilized Plaxis 2D software for 2D modeling. This software is designed to solve problems using the finite element method (FEM). As a starting point, a tunnel of diameter 5 m, as an existing tunnel, was modeled according to Figure 1 and its effects were examined. To investigate the effect of the new tunnel, the deformations of soil due to the existing tunnel in the first phase were set to zero, and only the soil deformations caused by the excavation of the new tunnel were considered. The position of the two tunnels is shown in Figure 1. In this context, the distance between the centers of the two tunnels was considered as a distance parameter.

2.2. Materials

Table 1 shows the characteristics of soils in different layers. The soil profile is taken from a soil profile located in eastern Victoria, Australia, in the Gippsland region. Three types of clay and one type of sand were considered in this modeling. It was assumed that the tunnels were dug in the deepest clay layer. The linear elastic perfectly plastic Mohr–Coulomb was used for all types of soils.

Also, Table 2 represents the specifications of the lining of tunnels. In this table, E, A, and I are elastic modulus, area, and the elements second moment of area, respectively. Also, EI is the indicator of the stiffness. All tunnels simulated with the same specifications, except for the diameter, so that the effect of the tunnel diameter could be investigated. The type of model which was used for the cover was the elastic model. Also, plates were used to model the lining.

Table 3 presents the specifications of the designed models. Two parameters were investigated in this study: the distance and diameter of the new tunnel, on the deformation of the soil and the existing tunnel.

In the modeling process, the mesh size was changed and adopted according to the dimensions of the tunnel.

Table 1
The characteristics of soils in different layers

	Unsaturated unit weight (kN/m^3)	Saturated unit weight (kN/m^3)	Permeability coefficient (m/day)	Reference soil modulus's (kN/m^2)	Poisson ratio	Cohesion (kN/m^2)	Friction angle	Dilatancy angle
Clay	15	18	0.05	24,000	0.3	150	25	5
Sand	17	21	1	90,000	0.3	0.1	32	6
Deep Clay	16.5	20	0.01	75,000	0.3	130	25	5
Deep Clay 2	16	19	0.01	60,000	0.3	115	22	4

Table 2
The characteristics of lining

	EA (kN/m)	EI (kNm^2/m)
Clay	15	18
Sand	17	21
Deep clay	16.5	20
Deep clay 2	16	19

Table 3
The plan of FEM modeling

Model no.	Diameter (m)	Distance (m)
1	3	6
2		7
3		9
4		11
5	4	6
6		7
7		9
8		11
9	5	6
10		7
11		9
12		11

3. Mathematical Modeling

3.1. Multiple linear regression

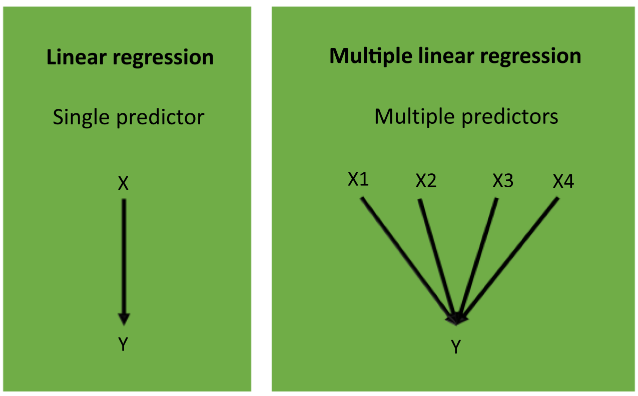
Using MLR, this statistical method predicts one output variable from multiple independent input variables. Figure 2 illustrates how MLR method is a developed version of linear regression that employs a single input and output variable.

It is assumed that the input parameters and output parameters are linearly related (Equation (1)) in MLR:

$$y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \varepsilon \tag{1}$$

In this equation, y is the predicted value, $\beta 0$ is the y-intercept when all other parameters are 0, X_1 and X_n are the first and last independent variables, β_1, β_n are the regression coefficients of the first and last independent variables, and ϵ is the model error.

Figure 2
The structure of multiple linear regression and linear regression



In MLR, the best line is obtained by selecting the regression coefficients that will result in the lowest error. The method of MLR was used prior to the development of CRRF model to evaluate the accuracy of MLR, as one of the simplest regression methods.

3.2. Classification and regression random forest

Random forests (RFs) were introduced by Breiman [29] as a decision tree-based method. A RF constructs a classification or regression tree by using different bootstrap samples based on the data, as well as changing the method by which they are constructed. Each node of a standard tree is split according to the best split among all variables. In a RF, each node is divided into subsets based on predictors that are randomly selected for that node. Despite expectations, this approach has proved to be quite effective compared to many other classifiers, including discriminant analysis, SVMs, and neural networks, and is resistant

Figure 3
Horizontal displacements for diameter = 3 m and (a) distance = 6 m, (b) distance = 11 m

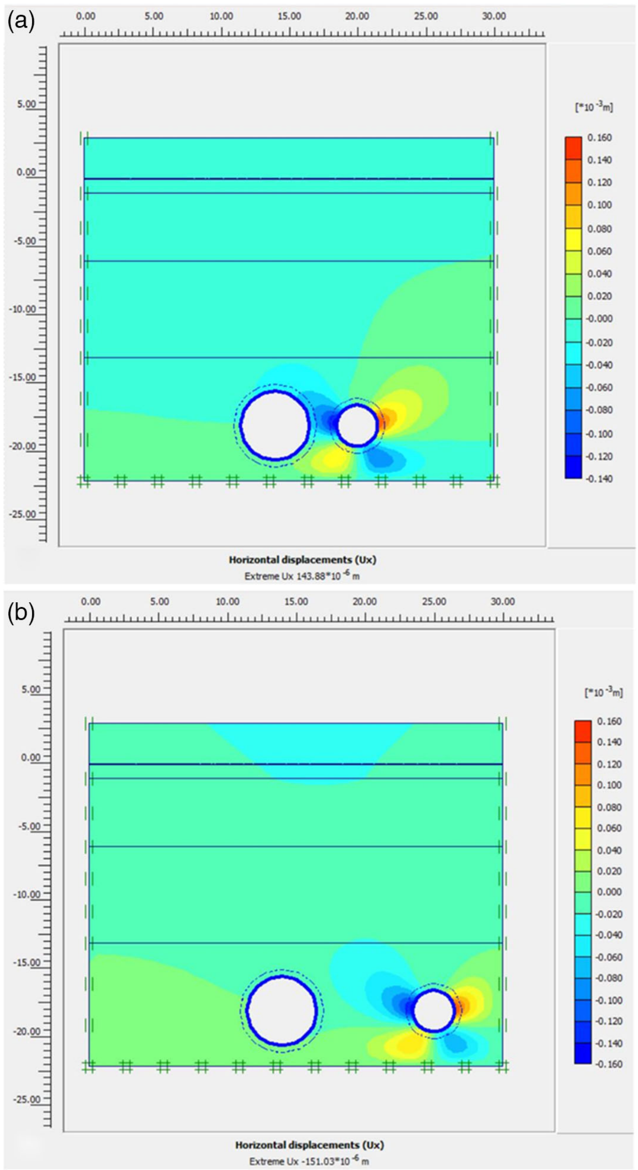


Figure 4
Horizontal displacements for distance = 6 m and (a) diameter = 3 m, (b) distance = 5 m

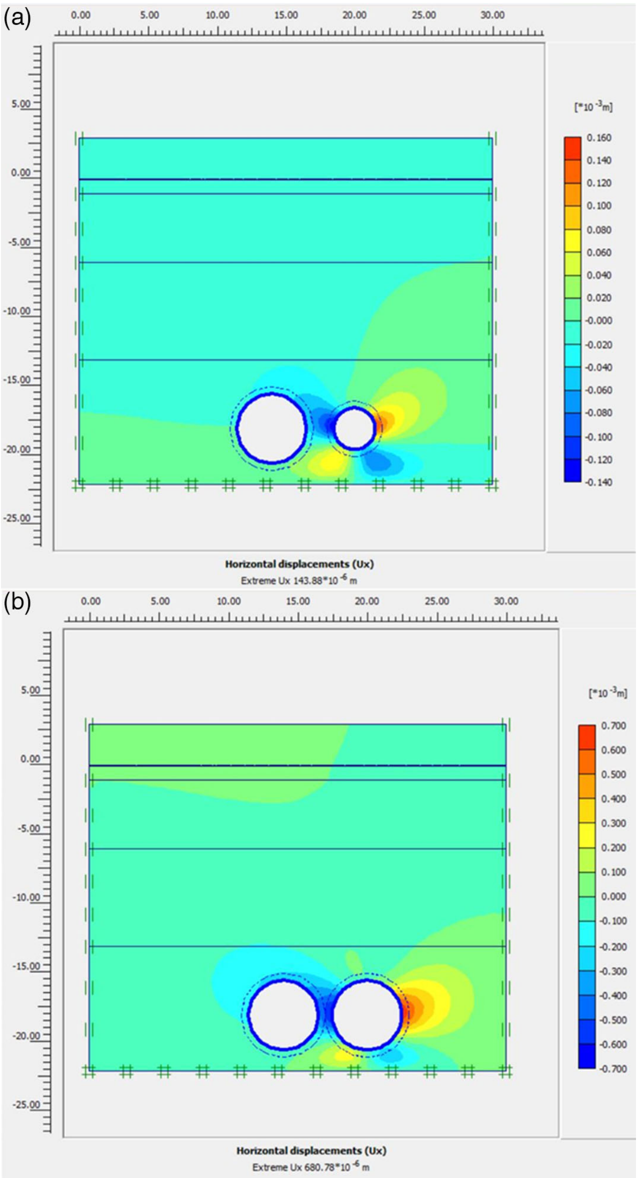
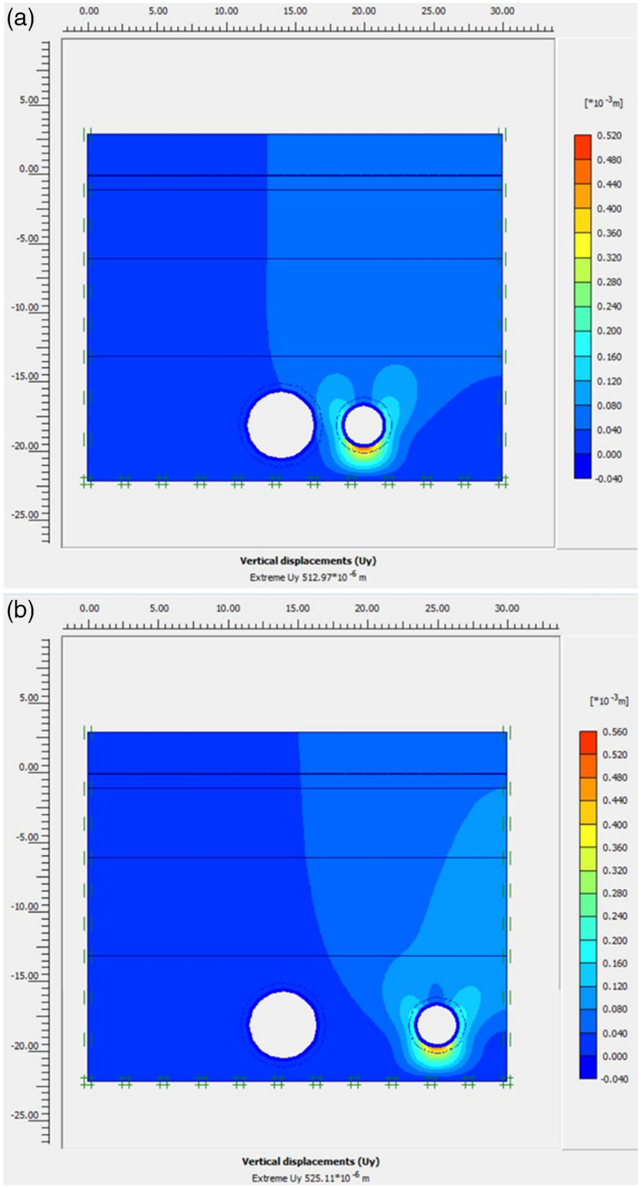


Figure 5
Vertical displacements for diameter = 3 m and (a) distance = 6 m, (b) distance = 11 m



to overfitting. Due to the fact that it has only two parameters, namely the number of random variables a node contains and the number of trees in the forest, it is also very user-friendly.

4. Results

4.1. Finite element method

The modeling process can generate two graphs, representing horizontal and vertical deformation. Results indicate only the new tunnel's effect on soil deformation under different conditions. A chart is displayed in two groups of results in this regard: displacements on the horizontal axis and displacements on the vertical axis.

4.1.1. Horizontal deformation

Figure 3 illustrates the displacement of the tunnels horizontally at distances of 6 and 11 m from the existing tunnel, when the new tunnel had a diameter of 3 m. It appeared that the presence of a new tunnel at a distance of 6 m from an existing tunnel had a significant impact on the horizontal displacement of the soil. There is a potential risk that the existing tunnel could be damaged as a result. In addition, if the new tunnel was dug at a distance of about 11 m from the existing tunnel, the results demonstrated that the effects of the new tunnel on the soil and then existing tunnel could still be observed. Therefore, designers must pay particular attention to this aspect of the design process.

Furthermore, Figure 4 shows the horizontal displacement between two tunnels in the case where the new tunnel had a diameter of 3 and 5 m and the distance between the two tunnels was 6 m. The results showed that when a new tunnel with a diameter of 3 m was located at a distance of 6 m from an existing tunnel, it could have a great impact on the horizontal displacement of the soil. The effects were multiplied if the new tunnel diameter was increased to 5 m and digging a new tunnel could cause significant damage to the existing tunnel.

Figure 6
Vertical displacements for distance = 6 m and (a) diameter = 3 m, (b) diameter = 5 m

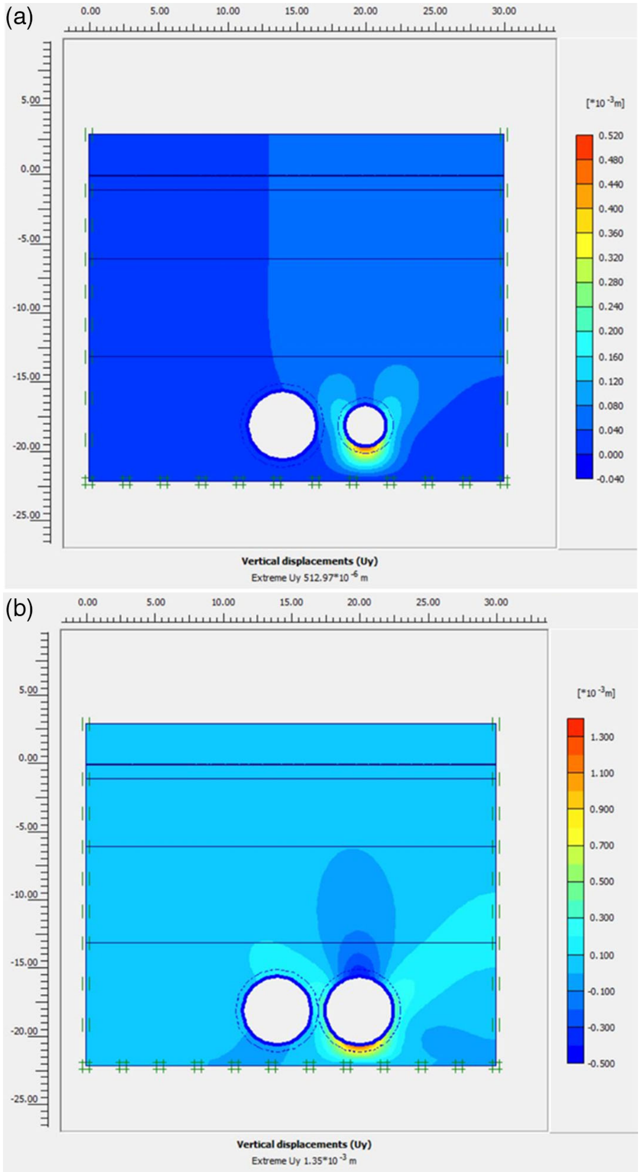


Table 4
The characteristics of soils in different layers

	Diameter	Distance	Horizontal displacement	Vertical displacement
Diameter	1	−0.07	0.43	0.27
Distance	−0.07	1	−0.40	−0.38
Horizontal displacement	0.43	−0.40	1	0.02
Vertical displacement	0.27	−0.38	0.02	1

Figure 7
The results of best multiple linear regression model

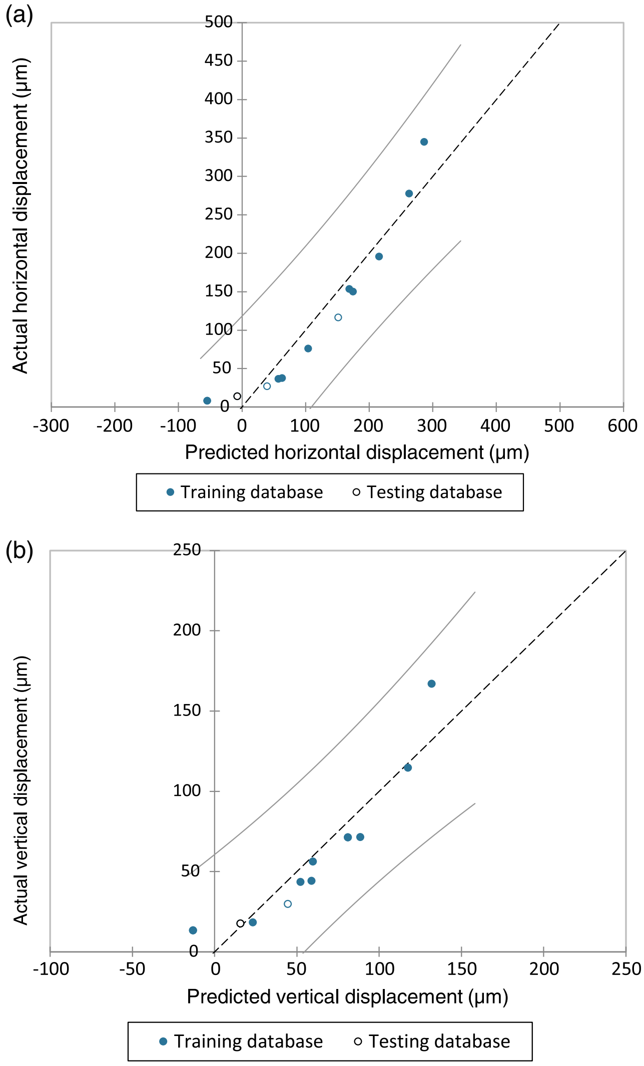


Table 5
The performance of the best MLR model to predict horizontal displacement

Statistic	Training database	Test database
R	0.85	0.82
MAE	101.51	112.10

Table 6
The performance of the best MLR model to predict vertical displacement

Statistic	Training database	Test database
R	0.87	0.85
MAE	105.71	98.12

4.1.2. Vertical deformation

Figure 5 depicts the vertical deformation of soil in relation to the diameter of the new tunnel, which was 3 m in diameter, and the distance between the new tunnel and the existing tunnel was 6 and 11 m, respectively. If the new tunnel is drilled parallel to the old tunnel (and the horizon), it is expected that there will be fewer vertical displacement changes compared to horizontal displacement changes. As a result of the models, it was evident that when a new tunnel with a diameter of 3 m was located 6 m away

Table 7
The specifications of the best CRRF

Trees parameters				Forest parameters			
Min. node size	Min. son size	Max depth	Mtry	CP	Sampling	Sample size	Number of trees
2	1	10	2	0.00001	Random with replacement	9	1000

Table 8
The performance of the best CRRF model to predict horizontal displacement

Performance metrics	Training database	Testing database
MAE	2.12	3.10
R	0.96	0.93

Table 9
The performance of the best MLR model to predict vertical displacement

Performance metrics	Training database	Testing database
MAE	1.56	2.89
R	0.97	0.94

from the existing tunnel, its effect on vertical soil displacement was significant but less than horizontal displacement changes. In the case of a distance of 11 m, the magnitude of the effect decreased.

It is shown in Figure 6 that there was a vertical deformation in the soil due to the construction of a new tunnel at a distance of 6 m from the existing tunnel and with two different diameters of 3 and 5 m. Results indicated that by digging a new tunnel with a diameter of 5 and 3 m, the vertical displacement increased by more than 250%.

4.2. Mathematical methods

4.2.1. Multiple linear regression

The generated database was divided into two training and testing databases, with 80% and 20% of the total database. Furthermore, two equations were used in order to evaluate the performance of the trained models: the correlation coefficient (R) (Equation (2)) and the mean absolute error (MAE) (Equation (3)) between the predicted and measured values.

$$R = \frac{\sum_N (X_m - \bar{X}_m)(X_p - \bar{X}_p)}{\sqrt{\sum_N (X_m - \bar{X}_m)^2 \sum_N (X_p - \bar{X}_p)^2}} \quad (2)$$

$$MAE = \frac{\sum_N |(X_m - X_p)|}{N} \quad (3)$$

where X_m, X_p, $\bar{X}_m$, $\bar{X}_p$ are actual values, predicted values, the average of actual values, and the average of predicted values, respectively, and N is the number of datasets. The best model is a model that has R of 1 and MAE equal 0.

Table 4 shows the Pearson correlation (r) matrix between the input parameters and the corresponding output parameters. Table 4 represents that there is no direct linear relationship between the input and output parameters, and in the best case, the Pearson correlation (r) is less than 0.5.

Figure 8
The results of best multiple linear regression model

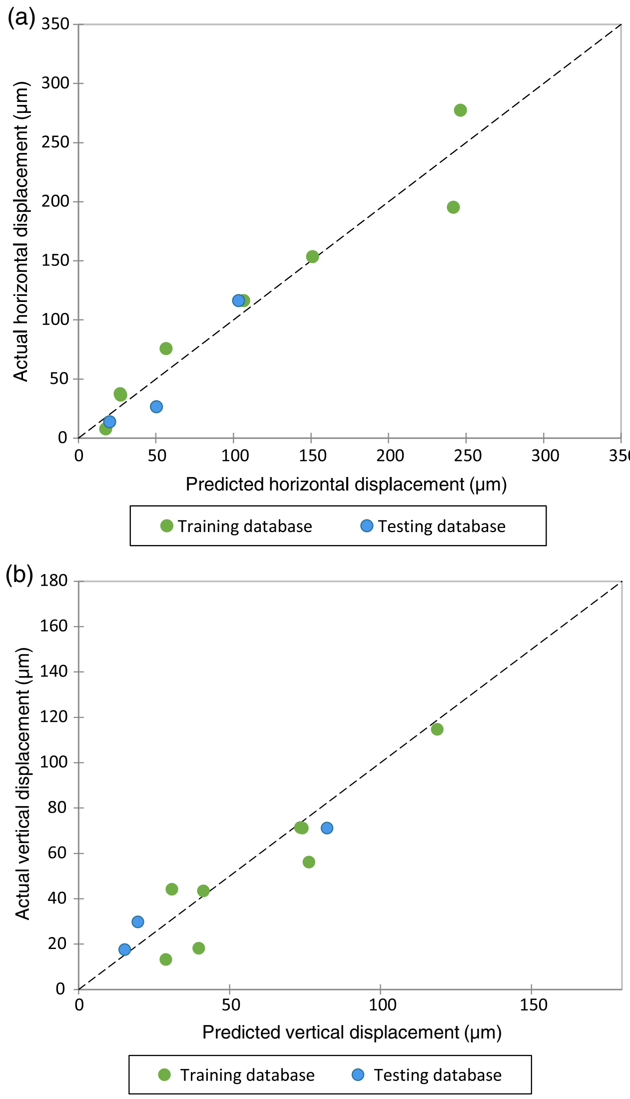


Figure 7 shows the results of the MLR model for the generated database (training and testing) based on actual values and predicted values for vertical and horizontal displacements.

Furthermore, Tables 5 and 6 present the results of MLR for predicting the two parameters of horizontal and vertical displacements, respectively. According to the results, the R and MAE of the best MLR model for predicting the horizontal displacement for the test database were 0.82 and 112.10, respectively. The test database's results for predicting the vertical displacement were 0.85 and 98.12, respectively. According to

Figure 9
Effect of diameter and distance of new tunnel on (a) vertical and (b) horizontal displacements of existing tunnel

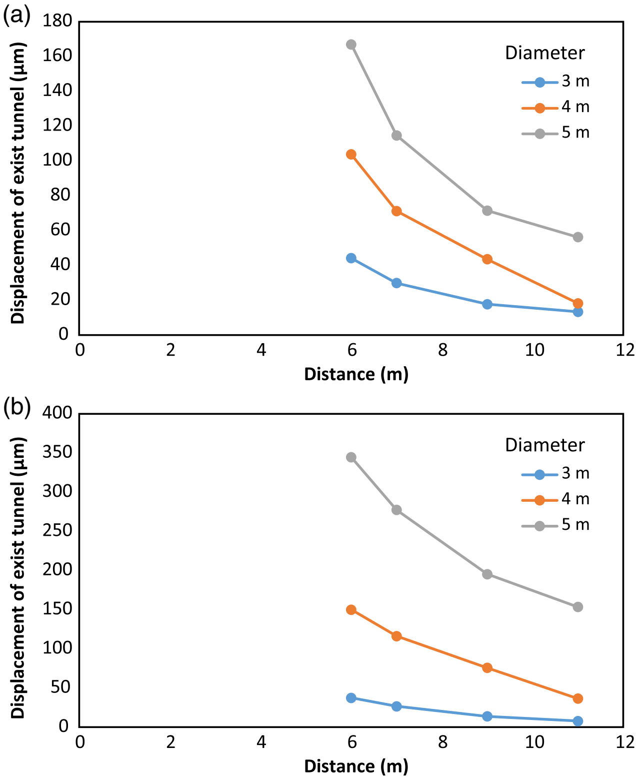
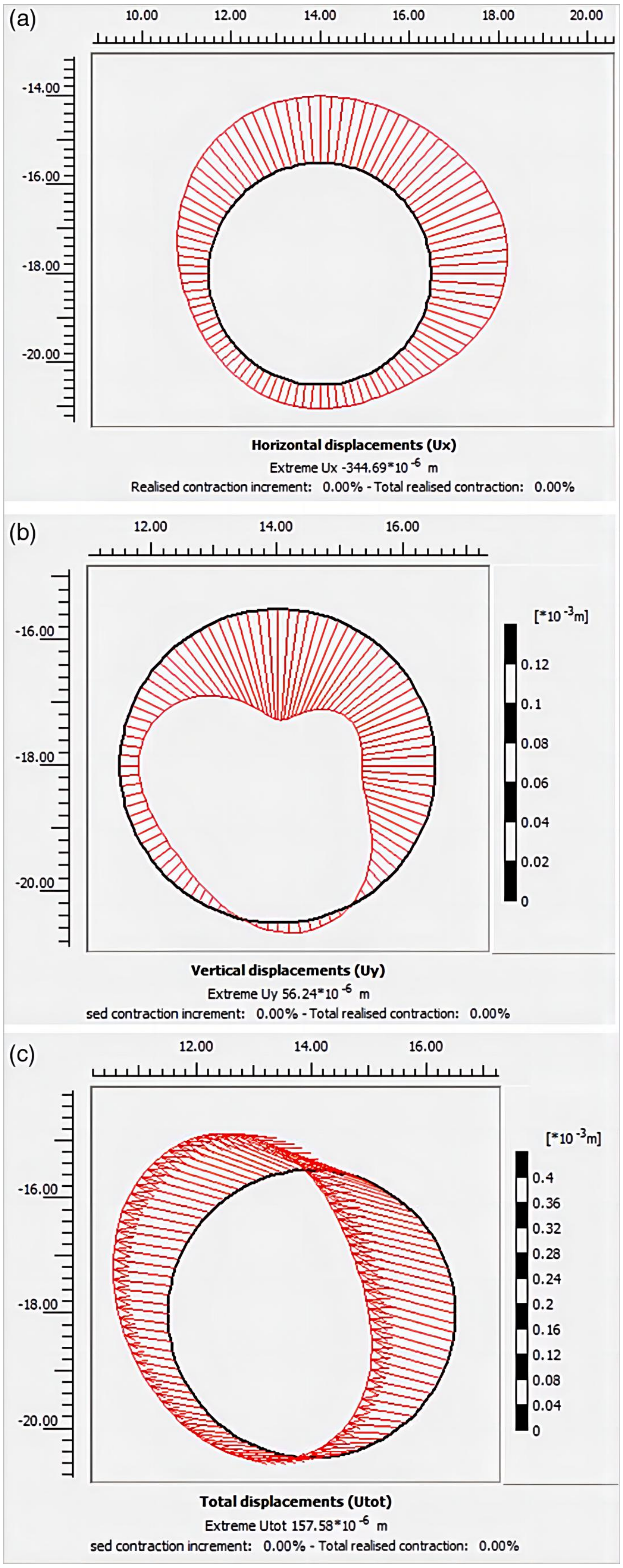


Figure 10
Displacements of existing tunnel for diameter = 5 m and distance = 6 m, (a) horizontal (b) vertical and (c) total displacements



these results, the MLR model is not very accurate in predicting horizontal and vertical displacements.

4.2.2. Classification and regression random forests

A series of analyses were performed to determine the best CRRF model for predicting the horizontal and vertical displacements. The specifications of the best CRRF model are shown in Table 7.

Table 4 indicates that the best number of tree depths was 10. In terms of time and accuracy, the depth of the tree has a significant impact on the model. It is because, as the depth of the tree increases, the accuracy of the model increases, but the model also takes longer to run. Therefore, it is very important to determine the optimum tree depth. Additionally, Table 4 indicates that the number of trees was 1000 and the sample size was 9. It should be noted that a large number of trees can increase the prediction time to some extent, and the number of 1000 was found to be the most efficient number from a time and accuracy perspective.

Tables 8 and 9 illustrate the results of the best decision tree network for predicting horizontal and vertical distances. Using the test database, the best CRRF model could predict the horizontal distance with R of 0.93 and MAE of 3.10, respectively. Moreover, the R and MAE of the best CRRF model for predicting the vertical displacement for the test database were 0.94 and 2.89, respectively. Based on these results, the CRRF model had a high degree of accuracy in predicting both output parameters.

Figure 8 compares the predicted and actual results for both output parameters. The model was able to accurately predict both outputs, as can be seen in the graph.

5. Discussion

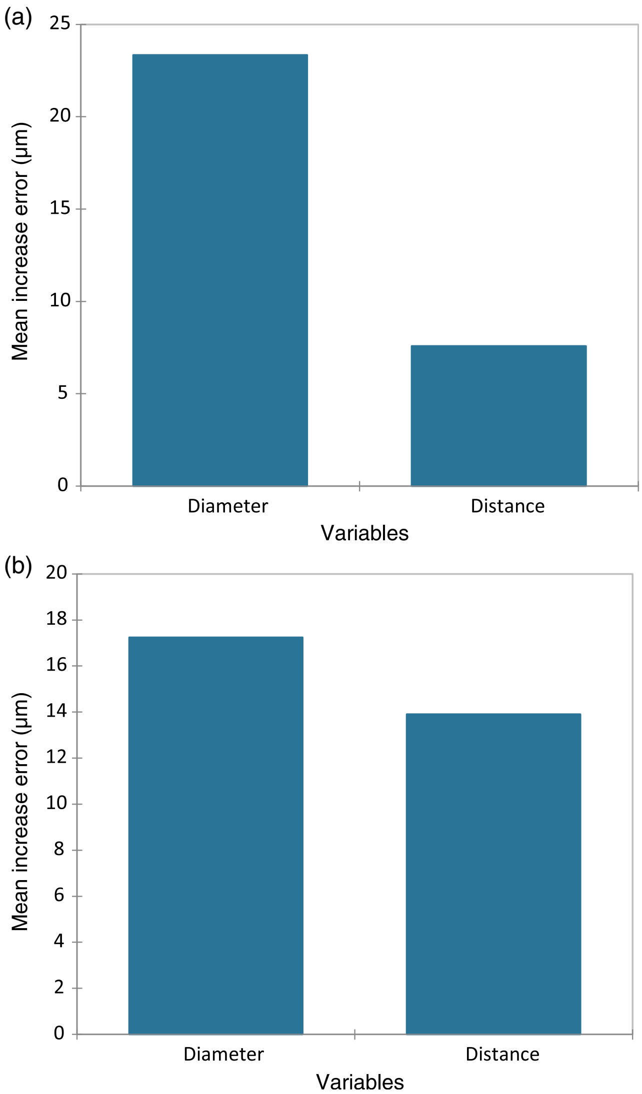
5.1. Comparison of FEM results

Figure 9 shows the effect of the new tunnel at different distances and diameters on the horizontal displacement of the existing tunnel. Results showed that the new tunnel caused 60% less horizontal and vertical displacement when it was 11 m away from the old tunnel than when it was 6 m away from the old tunnel. By increasing the diameter of the new tunnel from 3 to 5 m, on average, the horizontal and vertical displacement of the existing tunnel increased approximately 5 and 10 times, respectively. The results showed that the diameter of the new tunnel could have a significant impact on the horizontal and vertical displacements of the existing tunnel.

5.2. The worse scenario in FEM modeling

Figure 10 shows the effect of the new tunnel on the horizontal, vertical and total displacement of the existing tunnel. These diagrams were for the situation where the new tunnel with a diameter of 3 m was located at a distance of 6 m from the existing tunnel (the worst scenario). The results showed that the new tunnel had the greatest impact on the horizontal displacement of the existing tunnel and had the least impact on the vertical displacement of the tunnel.

Figure 11
Variable importance, the increase in mean error for (a) horizontal and (b) vertical displacement



5.3. Variable importance in CRRF modeling

This section examines the importance of the input parameters to the accuracy of the model. Figure 11 shows this topic based on the increase of mean error. To achieve this purpose, the input parameters were randomly varied from minimum to maximum and as a result of these changes, the CRRF model error was obtained. According to the results, the diameter of new tunnel played the most important role in predicting both horizontal and vertical distances.

6. Conclusion

In this study, the displacement of soil and the existing tunnel due to the excavation of a new tunnel were investigated for a multilayer soil using Plaxis 2D software, which uses the FEM. For this purpose, the effect of the diameter of the new tunnel and its distance from the existing tunnel was investigated. The results were expressed in two main parts, horizontal and vertical displacement. According to the results, the horizontal deformation of the existing tunnel was 37.54 and 7.89 µm because of digging the new tunnel with a diameter of 3 m at distances of 6 and 11 m, respectively, while the horizontal displacement of the existing tunnel was 344.69 and 153.5 µm because of digging the new tunnel with a diameter of 5 m at distances 6 and 11 m. The results showed that the effect of the new tunnel with the same diameter decreased by about 60% with increasing distance from 6 to 11 m, but the effect of the new tunnel was still evident at a distance of 11 m. Also, the effect of the diameter of the new tunnel showed that with the increase of the diameter from 3 to 5 m, the movements of the existing tunnel have increased approximately between 5 and 9 times, depending on its distance. This research showed that even tunnels with a diameter of 3 m and at a distance of 11 m from the existing tunnel significantly impacted the existing tunnel.

After examining the results of the numerical method, the existing database was used for the feasibility of using AI and mathematical methods. The results showed that the CRRF method as an AI method performed better than the MLR method with R of 0.93 and MAE of 3.10 to predict horizontal displacement and R of 0.94 and MAE of 2.89 to predict vertical displacement for the test database. Also, the sensitivity analysis and variable importance of the CRRF model showed that in the prediction of both horizontal and vertical displacements, the diameter of the new tunnel was the most influential parameter.

Regarding the limitations of the CRRF method, it should be noted that it is slow to predict due to the large number of trees. Although the method is fast for training the algorithm, it is a little slow for predicting results.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

References

[1] Baghbani, A., & Kashki, A. (2016). Evaluation of the ultimate carrying capacity of buried piles in soft clay due to changes in groundwater level with 3D modelling. In *5th International Conference on Geotechnical Engineering and Soil Mechanics*.

[2] Kimmance, J. P., Lawrence, S., Hassan, O., Purchase, N. J., & Tollinger, G. (1996). Observations of deformations created in existing tunnels by adjacent and cross cutting excavations. In *Geotechnical Aspects of Underground Construction in Soft Ground*, 707–712.

[3] Sahebzadeh, S., Heidari, A., Kamelnia, H., & Baghbani, A. (2017). Sustainability features of Iran's vernacular architecture: A comparative study between the architecture of hot–arid and hot–arid–windy regions. *Sustainability*, *9*(5), 749. https://doi.org/10.3390/su9050749

[4] Katebi, H., Rezaei, A. H., Hajialilue-Bonab, M., & Tarifard, A. (2015). Assessment the influence of ground stratification, tunnel and surface buildings specifications on shield tunnel lining loads (by FEM). *Tunnelling and Underground Space Technology*, *49*, 67–78. https://doi.org/10.1016/j.tust.2015.04.004

[5] Cooper, M. L., Chapman, D. N., Rogers, C. D. F., & Chan, A. H. C. (2002). Movements in the Piccadilly Line tunnels due to the Heathrow Express construction. *Géotechnique*, *52*(4), 243–257. https://doi.org/10.1680/geot.2002.52.4.243

[6] Mašın, D., & Herle, I. (2005). Numerical analyses of a tunnel in London clay using different constitutive models. In *Proceedings of the 5th International Symposium TC28 Geotechnical Aspects of Underground Construction in Soft Ground*, 595–600.

[7] Pan, Y., Liu, Y., Tyagi, A., Lee, F. H., & Li, D. Q. (2021). Model-independent strength-reduction factor for effect of spatial variability on tunnel with improved soil surrounds. *Géotechnique*, *71*(5), 406–422. https://doi.org/10.1680/jgeot.19.P.056

[8] Sui, C. Y., Shen, Y. S., Wen, Y. M., & Gao, B. (2021). Application of the modified Mohr–Coulomb yield criterion in seismic numerical simulation of tunnels. *Shock and Vibration*, *2021*, 9968935. https://doi.org/10.1155/2021/9968935

[9] Zareifard, M. R. (2020). Ground reaction curve for deep circular tunnels in strain-softening mohr–coulomb rock masses considering the damaged zone. *International Journal of Geomechanics*, *20*(10), 04020190. https://doi.org/10.1061/(ASCE)GM.1943-5622.0001822

[10] Liu, X., Matsubara, S., Yamada, S., & Kyoya, T. (2019). Numerical analysis of a tunnel in swelling rockmass by a modified cam-clay based model. In *5th ISRM Young Scholars' Symposium on Rock Mechanics and International Symposium on Rock Engineering for Innovative Future*.

[11] Wei, Y. H., Wang, Y. Q., Yue, M. A. O., Chen, L. L., & Wang, M. (2020). Influence of shield tunnel excavation on adjacent pile foundation based on modified cam-clay model. *Journal of Highway and Transportation Research and Development*, *14*(2), 84–92.

[12] Huang, Z., Zhang, H., Fu, H., Ma, S., & Liu, Y. (2020). Deformation response induced by surcharge loading above shallow shield tunnels in soft soil. *KSCE Journal of Civil Engineering*, *24*, 2533–2545. https://doi.org/10.1007/s12205-020-0404-8

[13] Jin, Y. F., Zhu, B. Q., Yin, Z. Y., & Zhang, D. M. (2019). Three-dimensional numerical analysis of the interaction of two crossing tunnels in soft clay. *Underground Space*, *4*(4), 310–327. https://doi.org/10.1016/j.undsp.2019.04.002

[14] Zheng, G., Wang, R., Lei, H., Zhang, T., Guo, J., & Zhou, Z. (2023). Relating twin-tunnelling-induced settlement to changes in the stiffness of soil. *Acta Geotechnica, 18*, 469–482. https://doi.org/10.1007/s11440-022-01541-5

[15] Avgerinos, V., Potts, D. M., & Standing, J. R. (2017). Numerical investigation of the effects of tunnelling on existing tunnels. *Géotechnique*, *67*(9), 808–822. https://doi.org/10.1680/jgeot.SiP17.P.103

[16] Barakat, M. A. (1996). *Measurements of ground settlement and building deformations due to tunnelling*. Doctoral dissertation, University of London.

[17] Cooper, M. L. (2001). *Tunnel-induced ground movements and their effects on existing tunnels and tunnel linings*. Doctoral dissertation, University of Birmingham.

[18] Standing, J. R., & Selman, R. (2001). 29 The response to tunnelling of existing tunnels at Waterloo and Westminster. In F. M. Jardine, J. B. Burland & J. R. Standing (Eds.), *Building response to tunnelling: Case studies from construction of the Jubilee Line Extension, London* (pp. 509–546). Thomas Telford Publishing.

[19] Zheng, G., Fan, Q., Zhang, T., & Zhang, Q. (2022). Numerical study of the Soil-Tunnel and Tunnel-Tunnel interactions of EPBM overlapping tunnels constructed in soft ground. *Tunnelling and Underground Space Technology*, *124*, 104490. https://doi.org/10.1016/j.tust.2022.104490

[20] Wang, H. N., Gao, X., Wu, L., & Jiang, M. J. (2020). Analytical study on interaction between existing and new tunnels parallel excavated in semi-infinite viscoelastic ground. *Computers and Geotechnics*, *120*, 103385. https://doi.org/10.1016/j.compgeo.2019.103385

[21] Addenbrooke, T. I., Potts, D. M., & Puzrin, A. M. (1997). The influence of pre-failure soil stiffness on the numerical analysis of tunnel construction. *Géotechnique*, *47*(3), 693–712. https://doi.org/10.1680/geot.1997.47.3.693

[22] Akbarzadeh, M., Shaffiee Haghshenas, S., Jalali, S. M. E., Zare, S., & Mikaeil, R. (2022). Developing the rule of thumb for evaluating penetration rate of TBM, using binary classification. *Geotechnical and Geological Engineering*, *40*(9), 4685–4703. https://doi.org/10.1007/s10706-022-02178-7

[23] Baghbani, A., Choudhury, T., Costa, S., & Reiner, J. (2022). Application of artificial intelligence in geotechnical engineering: A state-of-the-art review. *Earth-Science Reviews*, *228*, 103991. https://doi.org/10.1016/j.earscirev.2022.103991

[24] Guido, G., Shaffiee Haghshenas, S., Shaffiee Haghshenas, S., Vitale, A., Astarita, V., Park, Y., & Geem, Z. W. (2022). Evaluation of contributing factors affecting number of vehicles involved in crashes using machine learning techniques in rural roads of Cosenza, Italy. *Safety*, *8*(2), 28. https://doi.org/10.3390/safety8020028

[25] Shaffiee Haghshenas, S., Mikaeil, R., Abdollahi Kamran, M., Shaffiee Haghshenas, S., & Hosseinzadeh Gharehgheshlagh, H. (2019). Selecting the suitable tunnel supporting system using an integrated decision support system, (Case study:

Dolaei Tunnel of Touyserkan, Iran). *Journal of Soft Computing in Civil Engineering*, *3*(4), 51–66. https://doi.org/10.22115/scce.2020.212995.1150

[26] Feng, T., Wang, C., Zhang, J., Wang, B., & Jin, Y. F. (2022). An improved artificial bee colony-random forest (IABC-RF) model for predicting the tunnel deformation due to an adjacent foundation pit excavation. *Underground Space*, *7*(4), 514–527. https://doi.org/10.1016/j.undsp.2021.11.004

[27] Shi, S., Zhao, R., Li, S., Xie, X., Li, L., Zhou, Z., & Liu, H. (2019). Intelligent prediction of surrounding rock deformation of shallow buried highway tunnel and its engineering application. *Tunnelling and Underground Space Technology*, *90*, 1–11. https://doi.org/10.1016/j.tust.2019.04.013

[28] Wu, B., Qiu, W., Huang, W., Meng, G., Nong, Y., & Huang, J. (2022). A multi-source information fusion evaluation method for the tunneling collapse disaster based on the artificial intelligence deformation prediction. *Arabian Journal for Science and Engineering*, *47*, 5053–5071. https://doi.org/10.1007/s13369-021-06359-z

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

How to Cite: Baghbani, A., Baghbani, H., Shalchiyan, M. M., & Kiany, K. (2024). Utilizing Artificial Intelligence and Finite Element Method to Simulate the Effects of New Tunnels on Existing Tunnel Deformation. *Journal of Computational and Cognitive Engineering*, *3*(2), 166–175. https://doi.org/10.47852/bonviewJCCE2202307