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Enhancing Horizontal Displacement Prediction of Shoring Systems in Deep Urban Excavations Using Artificial Neural Networks

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Abstract This study aims to accurately predict the horizontal displacement of shoring systems in deep urban excavations, where numerous risks threaten the stability of surrounding structures. The methodology integrates Finite Element Modeling (FEM) to simulate soil behavior and excavation conditions, providing a detailed assessment of displacement under varying construction scenarios. The results from FEM serve as input for an Artificial Neural Network (ANN), which optimizes prediction accuracy by managing the nonlinear relationships between displacement factors. ANN predictions are then validated against actual field monitoring data, demonstrating significantly improved accuracy with low forecast errors and stable predictive capacity. By combining FEM and ANN, this research enhances predictive capabilities, offering a robust and feasible solution for optimizing shoring system design in deep excavations. Experimental results show that the proposed model achieves Mean Squared Error (MSE) = 0.0658, Root Mean Squared Error (RMSE) = 0.2566, and Mean Absolute Error (MAE) = 0.1835, proving its superiority over traditional methods. Additionally, feature importance analysis highlights the Y-coordinate and excavation depth as the most influential factors in displacement prediction, providing valuable insights into engineering applications. The findings also reveal that ANN is highly sensitive to input variations, particularly in FEM parameters such as elastic modulus and excavation depth. To improve generalization, future research should expand to various soil types and excavation conditions, ensuring broader applicability. Looking ahead, integrating deep learning techniques such as LSTM or CNN could further enhance real-time prediction and safety monitoring, ensuring more efficient and reliable excavation management in urban construction projects.

Keywords Finite Element Method, Artificial Neural Network, Horizontal Displacement Prediction, Geotechnical Engineering

1. Introduction

In the context of rapid urban development, deep excavation projects are increasingly common due to the demand for underground space for civil, commercial, and infrastructure constructions. However, deep excavation in urban areas presents significant challenges related to technical requirements and safety, especially in maintaining the stability of shoring systems to protect adjacent structures [1, 2]. The horizontal displacement of soil around excavations can cause deformation and subsidence in neighboring buildings, increasing the risk of damage and endangering the safety of both new and existing structures [3]. Therefore, accurately assessing and predicting the displacement of shoring systems are essential to ensure construction safety and efficiency, minimize risks, and optimize costs.

In recent years, numerous studies have been conducted to predict shoring system displacement using various analytical and modeling methods [4-6]. Finite element modeling (FEM) has been widely applied in geotechnical research to simulate and evaluate soil deformation in deep excavation projects [7]. FEM enables detailed analysis of influential factors such as soil properties, excavation depth, and shoring configuration, providing precise information about soil deformation [8-10]. However, this method may encounter accuracy limitations when dealing with complex soil conditions or nonlinear factors in real environments. For the FEM model, non-linearities are reflected through the stress-strain relationship of the soil. In addition, machine learning methods like artificial neural networks (ANN) have been studied and proven effective in handling the nonlinear relationships between input and output variables for displacement prediction, especially in cases that demand high accuracy [11-14]. Furthermore, Bayesian methods have also been used to update predictions over time based on monitoring data [15], and they require consistent data to achieve high accuracy. ANN also has significant limitations, including requiring a large amount of training data and the risk of overfitting if the number of parameters is not properly optimized.

Given the limitations of each individual method, this study aims to combine FEM and ANN models to enhance the accuracy of horizontal displacement prediction of shoring systems in deep urban excavation projects. Using analytical data from FEM as input for the ANN model not only optimizes predictive capabilities but also helps to overcome the limitations of each method when applied independently. Unlike previous studies, this research conducts feature importance analysis to identify key influencing factors, assisting engineers in the design and construction of shoring systems. Consequently, this research will provide an effective tool to assist designers and engineers in making decisions about shoring configurations, ensuring the safety of surrounding structures, and enhancing construction efficiency in complex projects.

2. Materials and Methods

The studied excavation site is located in an urban area with a soil profile predominantly consisting of mixed clay with an approximate thickness of 70 meters. This type of soil exhibits complex geotechnical properties, characterized by low bearing capacity and high susceptibility to deformation under the influence of loads and earth pressure. The groundwater table in the area lies at a depth of -4 meters, adding another layer of challenge to maintaining excavation stability during construction. The model assumes undrained conditions during the deep excavation phase to reflect the reality that, in the short term, the soil may not have enough time to drain, leading to an increase in pore water pressure and affecting soil deformation. Consequently, the shoring system must be carefully designed to ensure the safety of the excavation site and surrounding areas. Detailed geotechnical parameters for the simulation model include properties such as the unit weight of saturated soil ($\gamma sat = 20.57$ kN/m^3) and the elastic modulus E50ref, valued at 6875 kN/m^2, among other properties listed in Table 1. The Hardening Soil model describes the nonlinear relationship between stress and strain, accurately reflecting soil stiffness during compression, unloading, and reloading in deep excavation construction, and the mechanical properties of the soil are assumed as mean values to ensure the stability of the analytical model.

Table 1. Soil description parameters with Hardening soil model

Parameter	Value
Soil model	Hardening soil
Drainage	Undrained
Unit weight of water γ_w (kN/m^3)	20.25
Unit weight of saturated soil γ_{sat} (kN/m^3)	20.57
Initial void ratio e_{init}	0.5879
Initial porosity n_{init}	0.3702
E^{50}_{ref} (kN/m^2)	6875
E^{oed}_{ref} (kN/m^2)	6875
E^{ur}_{ref} (kN/m^2)	20.63E^3
Poisson's ratio V_{ur}	0.2
Power (m)	0.8
Reference pressure P_{ref} (kN/m^2)	38
Reference cohesion C'_{ref} (kN/m^2)	7.1
Effective internal friction angle φ' (degree)	30.40
Dilation angle Ψ (degree)	0.4

The FEM model was developed to simulate horizontal soil displacements under the influence of the shoring system in a typical deep urban excavation with dimensions of 12 x 40 x 16 meters (length, width, depth), as shown in Fig. 1. The finite element method (FEM) was employed to analyze soil displacements using the established technical parameters for the soil and shoring system [16-18]. The soil was modeled under undrained conditions, adhering to a hardening soil model, with each excavation stage proceeding at successive depths of -2.5m, -5.5m, -8.5m, -11.5m, and -16m. At each depth, the shoring system (-2m, -5m, -8m, and -11m) was activated to maintain stability, and horizontal displacements UX and UY were recorded to assess soil deformation levels at each excavation stage.

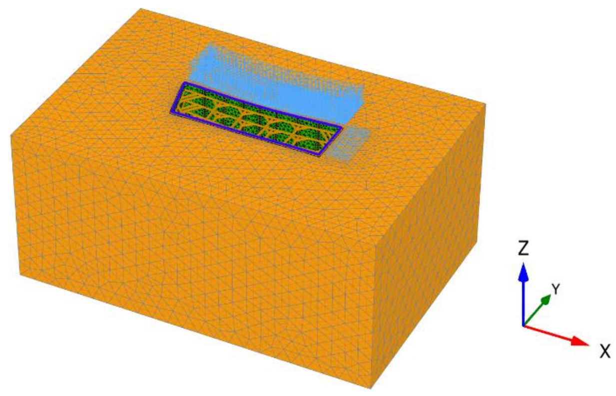

Figure 1. 3D Simulation of the Excavation

To enhance the prediction of horizontal displacements UX and UY for the shoring system, an artificial neural network (ANN) model was developed, where results from the FEM model served as input data [19, 20]. The data was divided into two sets: a training set and a testing set, with 80% of the data used for training and the remaining 20% for testing, ensuring the model's objectivity and accuracy. To optimize the input data, Standard Scaler was employed to normalize the data [21], reducing scale differences among parameters and improving model training efficiency.

The ANN model was designed with one input layer and three hidden layers, each configured with a decreasing number of neurons (64, 32, and 16 neurons) and utilizing the ReLU activation function to enhance nonlinearity within the model [22]. The output layer was structured to predict both horizontal displacement values, UX and UY, simultaneously optimizing the ANN's predictive capability for both displacement components. Model training proceeded through multiple epochs, with loss functions such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) applied to assess and optimize model error, minimizing the discrepancy between predicted and actual values. The convergence criteria in the ANN model were determined using the Adam optimization algorithm, with error reduction over 100 epochs.

Field monitoring data collected from the site was used to compare and evaluate the accuracy of the ANN model's predictions. Sensors were strategically positioned around the excavation site to measure horizontal displacements of UX and UY at various depths throughout the excavation process. The results from the ANN model were then compared with the monitoring data to assess accuracy, enabling an evaluation of the ANN model's effectiveness in simulating actual horizontal displacements. This process ensures that the model accurately reflects deformation phenomena under real-world construction conditions.

3. Results

The FEM analysis provides detailed data on horizontal displacements of UX and UY across different excavation depths, offering insights into the stability of the shoring system throughout the construction stages. Descriptive statistics indicate that the average horizontal displacement UX is -0.302 mm, with a standard deviation of 1.236 mm and a range from -7.691 mm to 6.020 mm, as shown in Fig. 2. For displacement UY, as shown in Fig. 3, the mean value is -5.210 mm, with a standard deviation of 10.133 mm, ranging from -38.676 mm to 18.725 mm, demonstrating greater variability than UX, as shown in Table 2.

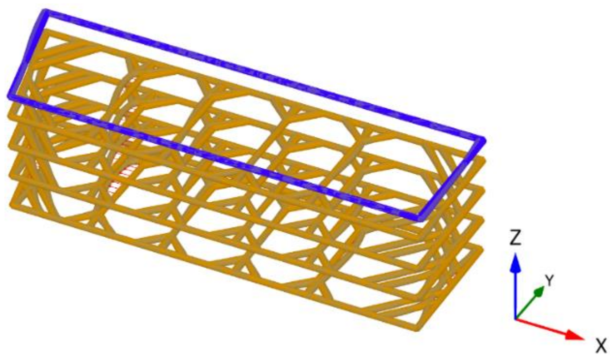

Figure 2. Total displacement UX at an excavation depth of -16m

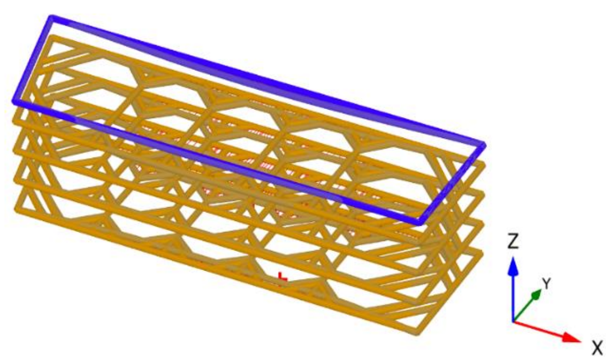

Figure 3. Total displacement UY at an excavation depth of -16m

Table 2. Descriptive statistics

Var	X (m)	Y (m)	Z (m)	UX (mm)	UY (mm)	Excavation Depth (m)
mean	0.481	0.068	-4.218	-0.302	-5.210	-11.824
std	12.733	4.992	3.281	1.236	10.133	3.718
min	-20.000	-6.000	-11.00	-7.691	-38.676	-16.000
0.250	-10.000	-5.572	-5.000	-1.110	-12.713	-16.000
0.500	0.100	0.139	-5.000	0.008	-1.394	-11.500
0.750	10.888	5.656	-2.000	0.480	1.069	-8.500
max	20.000	6.000	0.000	6.020	18.725	-5.500

Depth-specific analysis of UX and UY shows a clear trend, with displacement increasing as the excavation depth deepens. For instance, at a depth of -16 m, UX is -0.398 mm, and UY is -5.867 mm, whereas at a depth of -5.5 m, UX decreases to -0.196 mm, and UY is -4.009 mm, as shown in Table 3.

Table 3. Mean Horizontal Displacement by Excavation Depth

Excavation Depth (m)	UX (mm)	UY (mm)
-16	-0.398	-5.867
-11.5	-0.275	-5.222
-8.5	-0.229	-4.719
-5.5	-0.196	-4.009

This variation reflects the impact of earth pressure at different depths. Fig. 4 illustrates the trends in UX and UY displacements across depths, highlighting the increase in displacement with depth, which underscores the necessity of the shoring system to maintain structural stability during excavation.

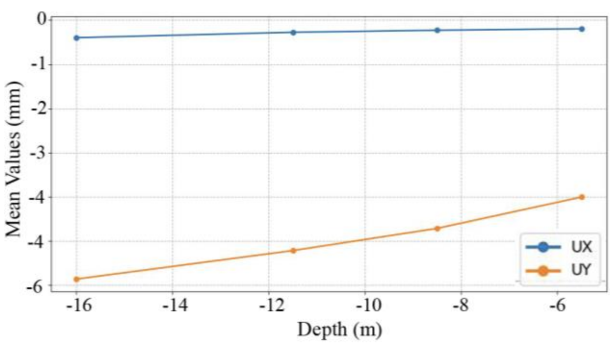

Figure 4. Trends of UX and UY by Depth

The ANN model achieved high prediction accuracy, as indicated by performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), with values of 0.0658, 0.2566 and 0.1835, respectively.

Feature importance analysis reveals that the Y-coordinate contributes the highest weight at 71.9472, followed by X at 28.298 and Z at 20.0539. Excavation depth also holds significant importance at 15.0115, while the influence of shoring layers (Active layer 1 to Active layer 4) is less pronounced, as shown in Table 4. This indicates that spatial position and depth are crucial factors in predicting the horizontal displacement of the shoring system, as shown in Fig. 5.

Table 4. Feature importance

Feature	Value
X	28.298
Y	71.9472
Z	20.0539
Depth	15.0115
Active shoring layer 1	2.642
Active shoring layer 2	6.226
Active shoring layer 3	7.112
Active shoring layer 4	5.3245

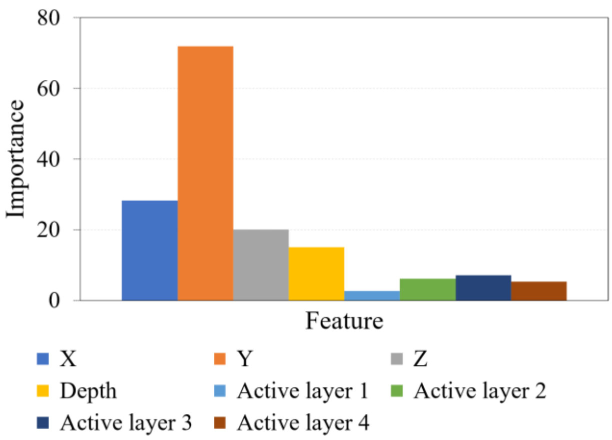

Figure 5. The Importance of Variables

Fig. 6 and Fig. 7 illustrate the optimization process of the ANN model across epochs, demonstrating the minimization of loss and improvement in MAE, while the error distribution plot shows that prediction errors are tightly controlled, reflecting stable accuracy, as shown in Fig. 8.

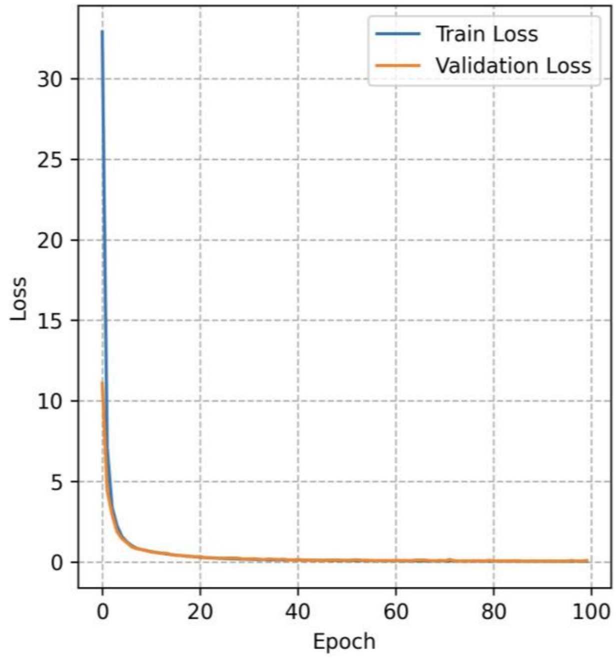

Figure 6. Loss

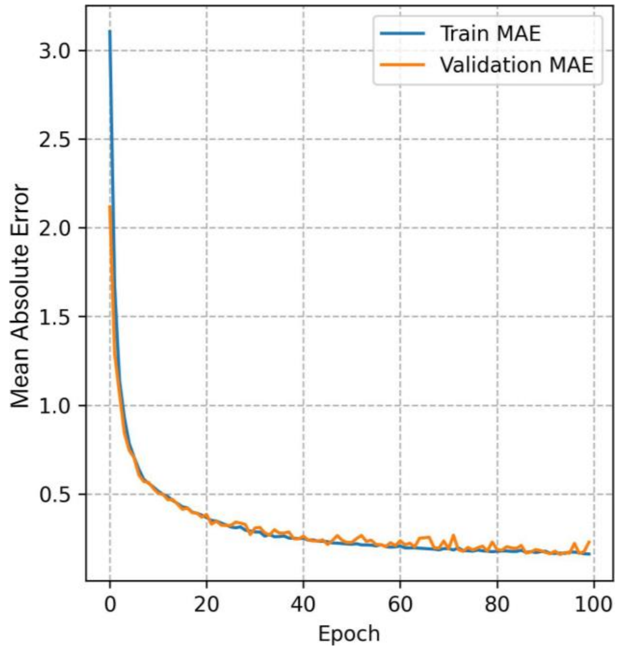

Figure 7. Mean Absolute Error

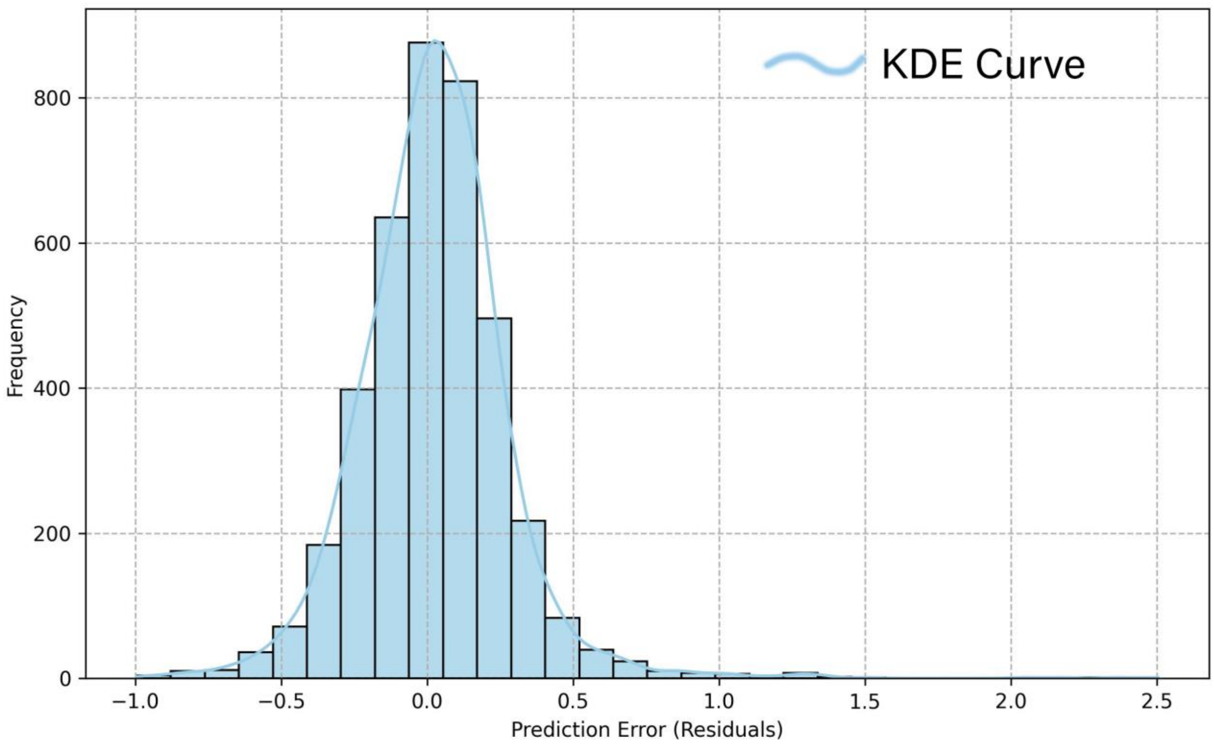

Figure 8. The error distribution

The ANN prediction results were compared in detail with field monitoring data for two critical positions, as shown in Fig. 9, A (X = 3.4 m, Y = 0 m, Z = -5 m) and B (X = 3.4 m, Y = 0 m, Z = -8 m), both located at an excavation depth of -16 m.

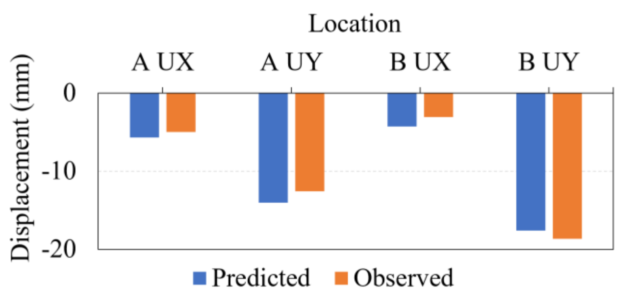

Figure 9. The ANN prediction results

At position A, the predicted UX value is -5.691 mm, while the observed value is -4.982 mm, yielding a deviation of 0.709 mm. Similarly, the predicted UY at position A is -14.002 mm, compared to the observed -12.544 mm, with a deviation of 1.458 mm, as shown in Table 5. At position B, the predicted UX is -4.281 mm, while the observed value is -3.074 mm, resulting in a deviation of 1.207 mm; the predicted UY is -17.583 mm, while the observed UY is -18.647 mm, with a deviation of -1.064 mm. These small deviations underscore the reliability and accuracy of the ANN model in predicting horizontal displacement, highlighting the method's effectiveness in optimizing the shoring system to ensure safety in deep urban excavations.

Table 5. Comparison Results

Location	Predicted		Observed		Difference	
	UX (mm)	UY (mm)	UX (mm)	UY (mm)	UX (mm)	UY (mm)
A	-5.691	-14.002	-4.982	-12.544	0.709	1.458
B	-4.281	-17.583	-3.074	-18.647	1.207	-1.064

4. Discussion

The results of this study demonstrate that the integration of FEM and ANN significantly enhances the accuracy of predicting horizontal displacement in shoring systems, contributing to safety in deep urban excavation projects. Using FEM data as input for ANN not only optimizes predictive capabilities but also minimizes errors caused by the nonlinear nature of the soil and complex real-world conditions. A comparison between ANN-predicted data and actual monitoring data shows that the model achieves Mean Squared Error (MSE) = 0.0658, Root Mean Squared Error (RMSE) = 0.2566, and Mean Absolute Error (MAE) = 0.1835, proving the high accuracy of the proposed method. However, the sensitivity of the ANN model to input data must be carefully considered, especially when FEM data varies due to different soil conditions and loading factors.

The study conducted a feature importance analysis to evaluate the influence of each parameter on horizontal displacement predictions. The results indicate that the Y-coordinate has the highest impact (71.95), followed by excavation depth (15.01) and the X-coordinate (28.30). While the shoring layers have lower impact scores, they still play a role in controlling soil deformation. This suggests that expanding the model to include various soil types and excavation conditions could significantly affect prediction outcomes. To improve generalization, the model can be extended by incorporating data from different soil types such as sand, weak clay, and mixed soil, allowing for a more comprehensive assessment of how soil properties influence shoring system displacement. Additionally, complex excavation conditions, such as multi-tiered shoring systems, asymmetrical excavations, and high groundwater table areas, should be incorporated into FEM modeling to provide diverse training datasets for ANN, thereby enhancing predictive accuracy under real-world construction scenarios.

Compared to previous studies, this research not only integrates FEM with ANN but also leverages FEM data for ANN training, enabling the model to learn the nonlinear relationship between stress and soil displacement. Poyraz and Vural [6] emphasized the role of slope angle and depth in displacement prediction for nailed retaining walls using machine learning methods but did not explore FEM integration to optimize predictions. Meanwhile, Chen et al. [5] applied Bayesian updating for time-dependent predictions, but their model requires continuous monitoring data to maintain accuracy. This study addresses that limitation by using FEM data as the primary input for ANN, ensuring the model remains stable even when monitoring data is limited.

Furthermore, to ensure practical applicability, it is essential to analyze the sensitivity of the ANN model to variations in input data. Experimental results indicate that changes in FEM parameters, such as the reference stiffness modulus (E50ref) or excavation depth, can cause ANN prediction errors to increase by up to 15% if the training data is not properly updated. This highlights the necessity for flexible model adjustments when applying ANN to different deep excavation conditions to maintain high accuracy. Besides, any numerical model is affected by epistemic uncertainties, leading to errors due to data limitations and model assumptions.

5. Conclusions

This study has demonstrated that integrating the Finite Element Method (FEM) with Artificial Neural Networks (ANN) significantly enhances the accuracy of predicting horizontal displacement in shoring systems for deep urban excavation projects. A comparison between ANN predictions and actual monitoring data shows that the model achieves low errors, with Mean Squared Error (MSE) = 0.0658, Root Mean Squared Error (RMSE) = 0.2566, and Mean Absolute Error (MAE) = 0.1835, proving the effectiveness of the proposed approach. Additionally, feature importance analysis indicates that the Y-coordinate and excavation depth are the most influential factors in prediction accuracy, providing crucial insights into optimizing shoring system design. Furthermore, the study reveals that the ANN model is highly sensitive to variations in input data, particularly when FEM parameters such as elastic modulus or excavation depth change. Experimental results indicate that prediction errors can increase if the training data is not properly updated, emphasizing the need for continuous model calibration with real-world data. Expanding the study to incorporate various soil types and excavation conditions would further improve the model's generalization capability.

In the future, integrating deep learning methods such as LSTM or CNN could enhance real-time prediction capabilities, thereby optimizing excavation safety monitoring and risk management in deep urban construction projects.

REFERENCES

[1] M. Buitrago, J. Sagaseta, and J. M. Adam, "Avoiding failures during building construction using structural fuses as load limiters on temporary shoring structures," *Engineering Structures*, vol. 204, p. 109906, 2020, doi: https://doi.org/10.1016/j.engstruct.2019.109906.

[2] M. Buitrago, J. Sagaseta, and J. M. Adam, "Effects of sudden failure of shoring elements in concrete building structures under construction," *Engineering Structures*, vol. 172, pp. 508-522, 2018, doi: https://doi.org/10.1016/j.engstruct.2018.06.052.

[3] S. Y. Lam, S. K. Haigh, and M. D. Bolton, "Understanding ground deformation mechanisms for multi-propped excavation in soft clay," *Soils and Foundations*, vol. 54, no. 3, pp. 296-312, 2014, doi: https://doi.org/10.1016/j.sandf.2014.04.005.

[4] A. E. Aboelela, A. M. Ebid, and A. L. Fayed, "Estimating the subgrade reaction at deep braced excavation bed in dry granular soil using genetic programming (GP)," *Results in Engineering*, vol. 13, p. 100328, 2022, doi: https://doi.org/10.1016/j.rineng.2021.100328.

[5] Chen, C., Zhan, L.-T., Chen, G.-N., Lyu, Y., Wu, T., Chen, Y.-M., and Liu, X.-W, "Bayesian updating of time-dependent diaphragm wall deflections in deep excavations in soft soils using different datasets," *Computers and Geotechnics*, vol. 173, p. 106499, 2024, doi: https://doi.org/10.1016/j.compgeo.2024.106499.

[6] S. Poyraz and İ. Vural, "Parametric Investigation of Corner Effect on Soil Nailed Walls and Prediction Using Machine Learning Methods," *Applied Sciences*, vol. 14, no. 16, 2024, doi: https://doi.org/10.3390/app14167331.

[7] Y. P. Dong, H. J. Burd, and G. T. Houlsby, "Finite-element analysis of a deep excavation case history," *Géotechnique*, vol. 66, no. 1, pp. 1-15, 2016, doi: https://doi.org/10.1680/jgeot.14.P.234.

[8] B.-C. B. Hsiung, K.-H. Yang, W. Aila, and L. Ge, "Evaluation of the wall deflections of a deep excavation in Central Jakarta using three-dimensional modeling," *Tunnelling and Underground Space Technology*, vol. 72, pp. 84-96, 2018, doi: https://doi.org/10.1016/j.tust.2017.11.013.

[9] T. X. Dang, P. T. Nguyen, T. A. Nguyen, and H. V. V. Tran, "Optimization of Barrette Wall Depths for Urban Excavation Stability Using FEM and ANOVA Testing," *Civil Engineering and Architecture*, vol. 12, no. 5, pp. 3530–3544, 2024. https://doi.org/10.13189/cea.2024.120529

[10] L. N. Vo, T. X. Dang, P. T. Nguyen, H. V. V. Tran, and T. A. Nguyen, "A Novel Methodological Approach to assessing Deformation and Force in Barrette Walls using FEM and ANOVA," *Engineering, Technology & Applied Science Research*, vol. 14, no. 5, pp. 16395-16403, 2024.

[11] Y. Wang, H. Tang, J. Huang, T. Wen, J. Ma, and J. Zhang, "A comparative study of different machine learning methods for reservoir landslide displacement prediction," *Engineering Geology*, vol. 298, p. 106544, 2022, doi: https://doi.org/10.1016/j.enggeo.2022.106544.

[12] H. D. Nguyen, N. D. Dao, and M. Shin, "Machine learning-based prediction for maximum displacement of seismic isolation systems," *Journal of Building Engineering*, vol. 51, p. 104251, 2022, doi: https://doi.org/10.1016/j.jobe.2022.104251.

[13] N. Xi, Q. Yang, Y. Sun, and G. Mei, "Machine Learning Approaches for Slope Deformation Prediction Based on Monitored Time-Series Displacement Data: A Comparative Investigation," *Applied Sciences*, vol. 13, no. 8, doi: https://doi.org/10.3390/app13084677.

[14] Nava, L., Carraro, E., Reyes-Carmona, C., Puliero, S., Bhuyan, K., Rosi, A., Monserrat, O., Floris, M., Meena, S. R., Galve, J. P., and Catani, F. "Landslide displacement forecasting using deep learning and monitoring data across selected sites," *Landslides*, vol. 20, no. 10, pp. 2111-2129, 2023, doi: https://doi.org/10.1007/s10346-023-02104-9.

[15] L. Liu, H. Yin, T. Xiao, B. Yang, and S. Lacasse, "Ensemble learning for landslide displacement prediction: A perspective of Bayesian optimization and comparison of different time series analysis methods," *Stochastic Environmental Research and Risk Assessment*, vol. 38, no. 8, pp. 3031-3058, 2024, doi: https://doi.org/10.1007/s00477-024-02730-2.

[16] A. Ray, R. Rai, A. Jaiswal, D. Dagdi, and A. K. Jha, "Numerical Modelling of Shoring Systems: Case Study," in *Proceedings of Geotechnical Challenges in Mining, Tunneling and Underground Infrastructures*, Singapore, A. K. Verma *et al.*, Eds., 2022// 2022: Springer Nature Singapore, pp. 201-216.

[17] W.-C. Cheng, C. Ni James, and Y.-H. Cheng, "Alternative Shoring for Mitigation of Pier-Foundation Excavation Disturbance to an Existing Freeway," *Journal of*

Performance of Constructed Facilities, vol. 31, no. 5, p. 04017072, 2017, doi: https://doi.org/10.1061/(ASCE)CF.1943-5509.0001063.

[18] M. Abu-Farsakh, A. Ardah, and G. Voyiadjis, "3D Finite element analysis of the geosynthetic reinforced soil-integrated bridge system (GRS-IBS) under different loading conditions," *Transportation Geotechnics*, vol. 15, pp. 70-83, 2018, doi: https://doi.org/10.1016/j.trgeo.2018.04.002.

[19] D. K. Ray, T. Roy, and S. Chattopadhyay, "Skewness scanning for diagnosis of a small inter-turn fault in quadcopter's motor based on motor current signature analysis," *IEEE Sensors Journal*, vol. 21, no. 5, pp. 6952-6961, 2020.

[20] S. Karahan and C. Gokceoglu, "Assessment for shallow and large tunnel construction in weak ground conditions: Application of tunnel boring machines," *Deep Underground Science and Engineering*, vol. n/a, no. n/a, 2024, doi: https://doi.org/10.1002/dug2.12083.

[21] M. M. Ahsan, M. A. P. Mahmud, P. K. Saha, K. D. Gupta, and Z. Siddique, "Effect of Data Scaling Methods on Machine Learning Algorithms and Model Performance," *Technologies*, vol. 9, no. 3, doi: https://doi.org/10.3390/technologies9030052.

[22] G. Lin and W. Shen, "Research on convolutional neural network based on improved Relu piecewise activation function," *Procedia Computer Science*, vol. 131, pp. 977-984, 2018, doi: https://doi.org/10.1016/j.procs.2018.04.239.