Transportation Geotechnics 47 (2024) 101284

Contents lists available at ScienceDirect

Transportation Geotechnics

journal homepage: www.elsevier.com/locate/trgeo

Original Article

Predictive modeling of shallow tunnel behavior: Leveraging machine learning for maximum convergence displacement estimation

Danial Sheini Dashtgoli [a,b,*], Rasool Sadeghian [c], Ahmad Reza Mahboubi Ardakani [c], Hamid Mohammadnezhad [c], Michela Giustiniani [b], Martina Busetti [b], Claudia Cherubini [a,b]

[a] Department of Mathematics, Informatics, and Geosciences, University of Trieste, Italy
[b] National Institute of Oceanography and Applied Geophysics - OGS, Trieste, Italy
[c] Faculty of Civil, Water and Environmental Engineering, Shahid Beheshti University, Tehran, Iran

ARTICLE INFO

Keywords:
Unsupported shallow tunnel
Maximum convergence displacement
Machine learning
Boosting techniques
XGBoost

ABSTRACT

Accurate prediction of maximum convergence in unsupported, shallow tunnel construction is crucial for optimizing the lining and ensuring tunnel safety. Machine learning (ML) algorithms, especially through boosting techniques, enable effective solution of complex engineering problems and demonstrate their capabilities in problem solving and optimization. In this study, the FLAC 3D package was used to create a robust and validated database of 954 datasets. Five tree-based ML algorithms, including extreme gradient boosting (XGBoost), adaptive boosting (AdaBoost), gradient boosting machine (GBM), histogram-based gradient boosting (HGB) and categorical boosting (CatBoost), were used to predict the maximum convergence displacement for unsupported shallow tunnels. For the test dataset, XGBoost outperformed the other models with an excellent coefficient of determination of 0.9633, a minimum mean absolute error of 0.0021 and a low root mean squared error of 0.00725. HGB followed closely behind, and GBM and CatBoost showed strong performances, while Adaboost was less effective. The superior performance of XGBoost highlights its effectiveness in predicting maximum convergence in shallow tunnels. An in-depth sensitivity analysis within the XGBoost model showed the significant influence of soil elastic modulus on the maximum convergence displacement in unsupported tunnels. The remarkable results achieved by the XGBoost algorithm on our complex tunnel convergence predictions illustrate the profound ability of ML to tackle complicated geotechnical challenges. This interdisciplinary collaboration demonstrates the potential of advanced algorithms to improve safety and efficiency in construction, underlining the crucial role of technology in tackling complex problems and establishing a new paradigm for innovation in the field.

Introduction

Tunneling is a complex process that involves the excavation of underground passages for transportation, water supply, and other purposes. One of the critical challenges in tunnel construction is predicting the maximum convergence of shallow tunnels, which is the amount of deformation or displacement that occurs in the surrounding soil or rock mass during the excavation process. The key to a secure and stable tunnel structure, while also enhancing the design and construction of the support system, lies in the accurate estimation of maximum convergence. The convergence displacements at the tunnel boundary occurs before the face progresses beyond a specific location. The tunnel boundary continues to undergo inward displacement as the tunnel advances beyond the mentioned point. This profile depicting closure or displacement concerning the distance from the tunnel face is termed the longitudinal displacement profile (LDP) [29]. Different researchers have done numerous studies considering ground properties [7,29,3,2,23], water effect [22,24,28], and other consideration including soil strength parameters [25]to approximate the LDP and tunnel displacement for unsupported tunnels.

While traditional methods for tunnel displacement calculations offer certain advantages, they come with significant disadvantages. These drawbacks include the high expenses associated with experiments, complexities in numerical modeling, and the necessity for oversimplified assumptions. In contrast, the integration of machine learning (ML) in tunnel engineering presents a more cost-effective and efficient solution. Nowadays, with advanced algorithms and powerful hardware,

* Corresponding author.
E-mail addresses: dsheinidashtgoli@ogs.it, danial.sheinidashtgoli@phd.units.it (D. Sheini Dashtgoli).

https://doi.org/10.1016/j.trgeo.2024.101284
Received 14 March 2024; Received in revised form 7 May 2024; Accepted 30 May 2024
Available online 1 June 2024
2214-3912/

Nomenclature

ABC Artificial Bee Colony: An optimization algorithm that simulates the foraging behavior of bees.
AI Artificial Intelligence: The simulation of human intelligence processes by machines, especially computer systems.
CMA Covariance Matrix Adaptation: An evolutionary strategy for optimizing complex nonlinear functions.
D Tunnel Diameter: The total width of the tunnel cross-section.
DPM Dynamic Programming Model: A mathematical model that simplifies decision-making processes by breaking them down into simpler, sequential stages.
Dis Convergence Displacement: The movement toward each other of the opposite sides of a tunnel, usually due to stress or pressure.
E Modulus of elasticity: A measure of the stiffness of an elastic material, defined as the ratio of stress (pressure or force per unit area) to strain (proportional deformation in an object).
EM Expectation Maximization: An iterative method for finding maximum likelihood estimates of parameters in statistical models.
ES Evolutionary Strategy: A methodology for solving optimization problems based on the concept of evolution.
FDM Finite Difference Method: A numerical technique used to approximate solutions to differential equations by using finite difference approximations.
FLAC Fast Lagrangian Analysis of Continua: A numerical modeling software used in geotechnical engineering for simulating soil and rock behaviors.
GBM Gradient Boosting Machine: A machine learning technique for regression and classification problems.
H Depth of the Tunnel: The vertical distance from the surface to the crown of the tunnel.
HGB Histogram-Based Gradient Boosting: A machine learning technique for constructing decision trees.
K_0 Coefficient of Earth Pressure at Rest: The ratio of horizontal effective stress to vertical effective stress in soil at rest.
LDP Longitudinal Displacement Profile: A representation of displacement values measured along the length of the tunnel.
LSTM Long Short-Term Memory: A type of recurrent neural network used in deep learning.
MAE Mean Absolute Error: A measure of errors between paired observations.
ML Machine Learning: A branch of artificial intelligence that involves the development of algorithms that can learn from data.
PCA Principal Component Analysis: A statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables.
RMSE Root Mean Square Error: A measure used to evaluate the difference between values predicted by a model and the values actually observed.
RVM Relevance Vector Machine: A type of sparse kernel machine used in machine learning.
SHAP SHapley Additive exPlanations: A method to explain individual predictions based on the contribution of each feature.
TBM Tunnel Boring Machine: A machine used to excavate tunnels with a circular cross section through a variety of soil and rock strata.
c Cohesion: A measure of the shear strength of soil or rock from intermolecular forces.
γ Unit Weight of the Soil: The weight per unit volume of soil, expressed in kN/m^3.
υ Poisson's Ratio: A measure of the Poisson effect, the ratio of transverse strain to axial strain in material.
φ Friction Angle: The angle of shearing resistance of the soil.

ML is widely applied in engineering, particularly in construction and design. Improved algorithms and enhanced computing capabilities enable ML to analyze complex databases, revolutionizing how engineers approach challenges in these fields [27].

In the field of tunnel construction, Wang et al. [32] focused on predicting the tunnel boring machine (TBM) advance rates; consequently, they utilized the principal component analysis (PCA) and the artificial bee colony (ABC) methods to develop a highly accurate PCA-Artificial neural networks-ABC model. Similarly, Wang et al. [31] employed biogeography-based multilayer perceptron neural network and biogeography-based support vector regression methods for TBM penetration rate forecasting, showcasing the effectiveness of integrated artificial intelligence (AI) techniques. In their exploration of TBMs in tunnel construction, Shan et al. [26] addressed performance prediction and settlement concerns using ML techniques. Furthermore, Li et al. [18] conducted a comprehensive review of TBM dataset outcomes, evaluating ML algorithms for performance prediction and efficiency optimization. Wang et al. [33] proposed a dynamic prediction model with the long short-term memory and Extreme Gradient Boosting (XGBoost) for TBM performance during shield tunneling. To predict tunnel deformation, Zhou et al. [35] implemented ML techniques and optimized the random forest model with various algorithms to forecast deformation around powerhouse caverns. Tunnel squeezing was explored as a time-dependent phenomenon impacting tunnel construction costs and timelines by Fathipour-Azar [11]. The study developed a multi-level data mining decision-making assessment methodology based on parameters like diameter, buried depth, support stiffness, and rock tunneling quality index to predict squeezing conditions. The multi-level decision-making models achieved high prediction accuracy, providing effective tools for analyzing and mitigating tunnel squeezing problems. Later, Geng et al. [15] harnessed the power of Bayesian optimization and the entropy weight method to refine XGBoost model. Through the optimization of key hyperparameters, the study attained remarkable accuracy in predicting tunnel squeezing intensity. This investigation stands as a valuable resource for forecasting tunnel squeezing deformation, thereby enhancing the realm of intelligent tunneling operations.

For predicting tunnel convergence, Chang et al. [8] introduced a probabilistic model, combining empirical models (EM), Bayesian estimation, and relevance vector machine (RVM). By selecting the most accurate EM through Bayesian estimation and refining predictions with RVM, the model significantly reduced root mean squared error values by 92.6 % and 95.8 % for two datasets in a high-speed railway tunnel. Compared to alternative models like backpropagation neural network and Gaussian process regression, the presented model demonstrated superior accuracy, as reflected in the numerical results.

The prediction of convergence displacement in unsupported shallow tunnels has been a less explored area in the past. For geotechnical engineers, a precise understanding of convergence displacement is crucial. Previous studies have not extensively investigated the accuracy of ML models, especially those employing tree-based and boosting methods, in

Table 1
Properties for model validation.

Property	Value
Modulus of elasticity (E)	80 MPa
Friction angle	33 degrees
Internal cohesion	22 kPa
Poisson's ratio	0.29
Tunnel diameter	5 m
Density (γ)	19 KN/m^3
Depth of tunnel center	20 m

Table 2
Comparison of numerical validation model results with analytical results.

Parameter	FLAC 3D	Analytical equation [17]
Convergence displacement (cm)	4.87	4.8

predicting convergence displacement along the LDP. This study addresses a gap by assessing the performance of different tree-based ML algorithms through boosting for predicting convergence displacement in unsupported shallow tunnels. Five tree-based boosting algorithms are used to predict the convergence displacement of the tunnel. With the help of FLAC 3D, a database was created in which the essential parameters influencing tunnel convergence are considered. Key factors such as the unit weight of the soil (γ), the earth pressure coefficient at rest (K_0), the tunnel depth (H), the diameter (D), the Poisson's ratio (υ), the modulus of elasticity (E), the cohesion (c) and the friction angle (φ) were taken into account. A practical range was defined for each property and 954 finite difference models were simulated to accurately map their relationships to each other and thus accurately predict the convergence displacement (Dis). Based on this extensive database, five prediction models are applied to estimate the convergence displacement. The results highlight the model's effectiveness in predicting tunnel displacement. Finally, we rank the factors influencing displacement and offer a brief summary of our findings.

Methodology for database generation

Base model and calibration

Due to the necessity arising from the lack of sufficient and reliable data, a pragmatic solution is to create a thorough and extensive dataset through numerical modeling. In order to obtain a reliable database, numerical modeling with the software FLAC 3D (Itasca, 2003) was used in this study. First to validate the outcomes generated by FLAC 3D, a comparison is made with analytical equation by Hoek [17] and compared with the result of FLAC3D. Table 1 shows the properties considered for the model validation, while Table 2 illustrates a comparison between the results of the analytical solutions and FLAC 3D. As can be seen, the convergence displacement calculated by the FLAC 3D software can be considered acceptable compared to the analytical equation of Hoek [17]. Here are the relevant equations:

$$\text{Convergence displacement} = \frac{r_0(1+\vartheta)}{E} \times \left[2(1-\vartheta)(P_0 - P_{cr})\left[\frac{r_p}{r_0}\right]^2 - (1 - 2\vartheta)(P_0 - P_i)\right] \tag{1}$$

$$r_p = r_0\left[\frac{2(P_0(K-1)+\sigma_{cm})}{(1+K)\ ((K-1)P_i+\sigma_{cm})}\right]^{\frac{1}{K-1}} \tag{2}$$

$$P_{cr} = \frac{2P_0 - \sigma_{cm}}{1+K} \tag{3}$$

$$\sigma_1 = \sigma_{cm} + K\sigma_3 \tag{4}$$

The uniaxial compressive strength of the rock mass σ_{cm} is characterized by:

$$\sigma_{cm} = \frac{2c\ Cos(\varphi)}{(1-Sin\varphi)} \tag{5}$$

The gradient K in equation (4) is as follows:

$$K = \frac{1+Sin\varphi}{1-Sin\varphi} \tag{6}$$

Where:
σ_1: axial stress leading to failure.
σ_3: constricting stress.
c: internal cohesion.
φ: friction angle of the rock mass.
ϑ : Poisson's ratio.

Database overview

To ensure the accuracy of the finite difference method (FDM), a numerical model of 60 m × 35 m × 20 m was used to build the database. It included various parameters such as soil elastic modulus, Poisson's ratio, friction angle, cohesion, tunnel diameter, and soil overburden, using a three-dimensional numerical analysis. The LDP was determined, and the maximum convergence displacement at a distance of 3 times the tunnel diameter was set as the target value. The conceptual 3D model, which serves as the main model, is shown in Fig. 1.

Table 3 provides a comprehensive overview of the dataset, which

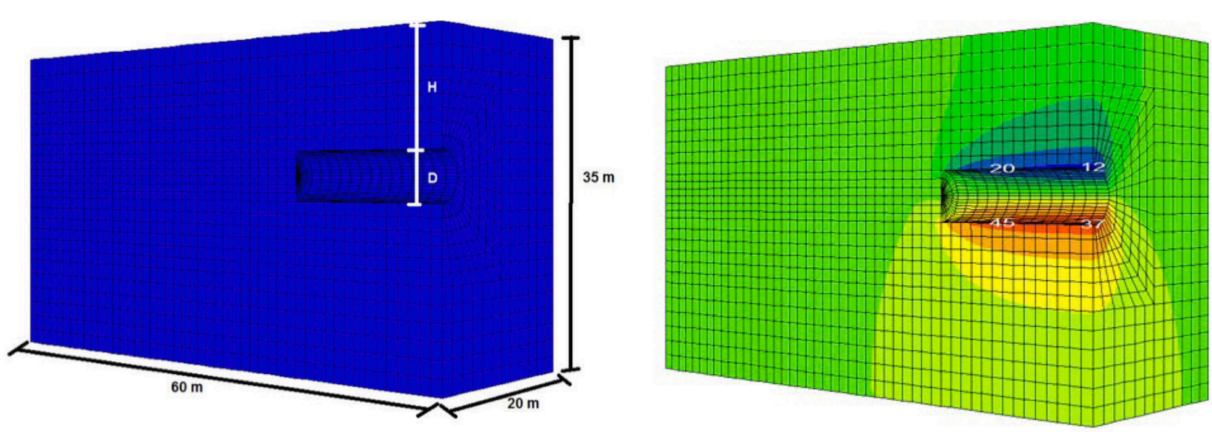

Fig. 1. 3D numerical model of shallow tunnel.

Table 3
Statistical summary of the input and output variables.

	γ (KN/m^3)	K_0	H	D (m)	υ	E (MPa)	c (KPa)	ϕ	*Displacement* (m)
count	954	954	954	954	954	954	954	954	954
mean	19.78	0.39	15.98	5.03	0.28	143.9	41.4	25.0	0.047
std	0.82	0.02	2.32	0.82	0.01	74.9	17.3	5.8	0.050
min	18.50	0.37	11.00	4.00	0.27	10.0	10.0	14.0	0.009
25 %	19.12	0.37	13.50	4.00	0.27	80.0	26.0	20.0	0.022
50 %	19.50	0.39	17.00	5.00	0.2	120.0	40.0	26.0	0.030
75 %	20.50	0.41	17.50	6.00	0.29	200.0	59.0	30.0	0.047
max	21.50	0.43	18.00	6.00	0.30	450.0	100.0	35.0	0.569

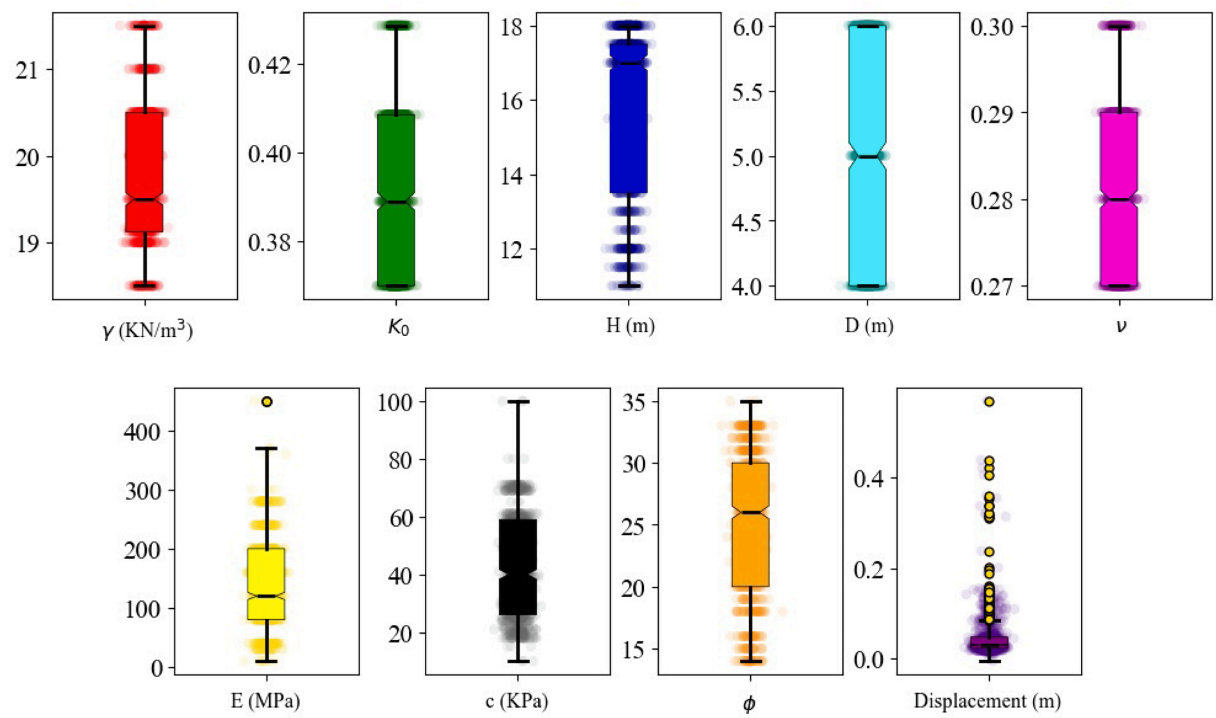

Fig. 2. Input and output variables box plot.

consists of 954 entries. It provides valuable statistical insights into the input and output variables. The table contains statistical measures for each parameter, such as mean, standard deviation (std), minimum (min), 25th percentile (25 %), median (50 %), 75th percentile (75 %), and maximum (max). These measures give a clear picture of the central tendency, variability, and range of values for the features, including unit weight of the soil (γ), coefficient of earth pressure at rest (K_0), depth of tunnel (H), tunnel diameter (D), Poisson's ratio (υ), modulus of elasticity (E), cohesion (c), friction angle (φ), and convergence displacement (Dis) as output. The mean values, for example, give an impression of the typical or average values, while the percentiles help to understand the data distribution over different quartiles.

Before using the dataset to train and test ML models, the identification of outliers was performed. Fig. 2 displays box plots representing both input and output variables. Although some outliers were identified, the dataset, gathered for the purpose of testing models to predict the convergence displacement of the tunnel, was considered appropriate.

The correlation matrix for the database reveals important insights into the relationships between different features and their effects on tunnel convergence (Fig. 3). When evaluating the correlation between each feature and the displacement, it can be seen that a moderately negative correlation is exhibited by unit weight of soil, implying that as unit weight increases, maximum convergence tends to decrease. The results show positive correlations, with higher values of K_0, tunnel depth, and Poisson's ratio being associated with greater convergence displacement of the tunnel. Conversely, a strong negative correlation is observed with the modulus of elasticity, indicating a lower maximum convergence displacement for materials with higher E values. Cohesion shows a weak negative correlation, indicating a slight reduction in maximum convergence with increased cohesion. In addition, there is a weak positive correlation with friction angle, implying that greater maximum convergence displacement may be associated with higher friction angle values. These correlations provide valuable insights for evaluating tunnel stability and making informed engineering decisions.

In Fig. 4 scatter plots were used to illustrate the relationships between the convergence displacement and each feature. A close examination of these scatter plots shows that they do not consistently exhibit clear patterns. However, one significant pattern stands out: There is a clear downward trend in the relationship between the modulus of elasticity and the convergence displacement. This downward trend implies that as the modulus of elasticity increases, the displacement tends to decrease, suggesting that materials with higher E values are associated with a lower maximum convergence displacement in shallow tunnels. In contrast, when considering the remaining features such as density, lateral earth pressure coefficient, tunnel depth, depth, Poisson's ratio, cohesion, and friction angle, no distinct or consistent trends can be identified from the scatter plots.

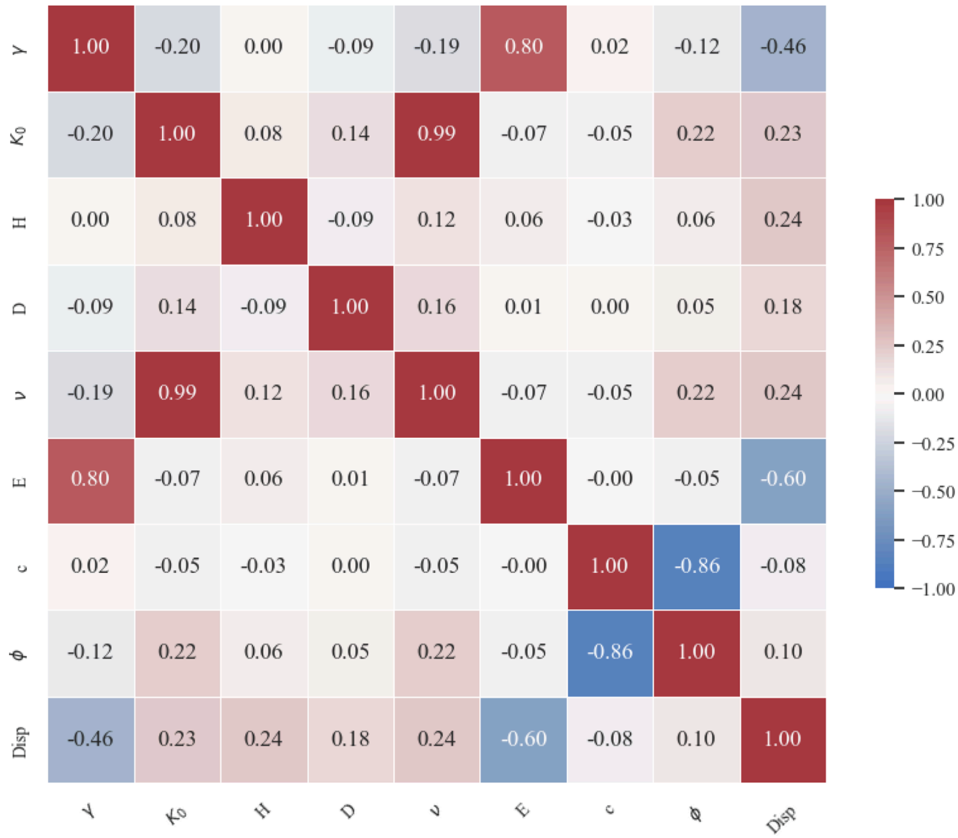

Fig. 3. Correlation matrix.

Workflow

The training of ML models involved utilizing input features including density, K_0, H, Poisson's ratio, E, c, and friction angle. Fig. 5 visually illustrates the fundamental processes of the proposed methodology, where the convergence displacement is the target variable.

Training process

The numerical dataset for the convergence displacement of shallow tunnels consists of 954 data points, generated based on a validated numerical modeling approach for FDM. The dataset was split into a training (80 %) and a test (20 %) subsets. Both sets were used during the training and validation phase to develop the ML models. This split allowed a comprehensive evaluation of the performance of the models.

ML algorithms and optimization

Boosting is a powerful technique used in tree-based algorithms to improve their prediction performance. This ensemble learning method focuses on sequentially training weak learners, usually decision trees, and combining their results to build a robust and accurate model [14]. In this comprehensive study, a series of ML models were used to predict the convergence displacement of shallow tunnels. The methodology included various boosting tree-based algorithms, each of which brings contributing its own strengths to the predictive power of the model. Among these, XGBoost, Adaptive Boosting (ADABoost), Gradient Boosting Machine (GBM), Histogram-based Gradient Boosting (HGB), and Categorical Boosting (CatBoost) were used as the main models. XGBoost is used due to its efficient implementation of gradient-boosted decision trees that sequentially build models to minimize prediction errors. ADABoost complements this approach by iteratively adjusting the weights to correct errors from previous predictions and thus improve the accuracy of the model. GBM further refines this process by creating trees that specifically address and reduce the residuals left by their predecessors. Meanwhile, HGB optimizes the efficiency of GBM by using histograms to speed up the calculation process, which is beneficial when managing large data sets typical for regression analysis. Finally, CatBoost is included due to its innovative treatment of categorical features through ordered boosting, which prevents overfitting and improves the reliability of the model by systematically reducing prediction errors over randomly permuted data segments. Together, these algorithms form a comprehensive ensemble that utilizes their individual strengths in a unified prediction model to achieve high accuracy of regression results. In particular, XGBoost, known for its efficiency and speed, works together with ADABoost, which focuses on the iterative correction of errors to improve prediction accuracy. GBM, an ensemble learning method, has teamed up with HGB and uses histogram-based strategies to increase efficiency. Finally, CatBoost, designed for seamless processing of categorical features, added another layer of sophistication to the ensemble. This fusion of boosting tree-based algorithms underscores the commitment to a nuanced and robust approach to predicting the convergence displacement of shallow tunnels [5,9,10,13,14,20].

The Optuna package was utilized to fine-tune the hyperparameters of the models used [1].

The CmaEsSampler in Optuna is a practical implementation of the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) algorithm, a sophisticated optimization technique rooted in evolutionary strategies and stochastic optimization [16]. In this study, all modeling procedures were performed in Python 3.10.9, using open-source libraries such as CatBoost, XGBoost, Scikit-learn, Optuna, SHAP, Matplotlib, SciPy, Pandas, and NumPy.

ML model assessment

In the development of ML models, the validation phase is crucial for the evaluation of prediction accuracy. In this study, three key statistical indicators namely, the coefficient of determination (R^2), root mean

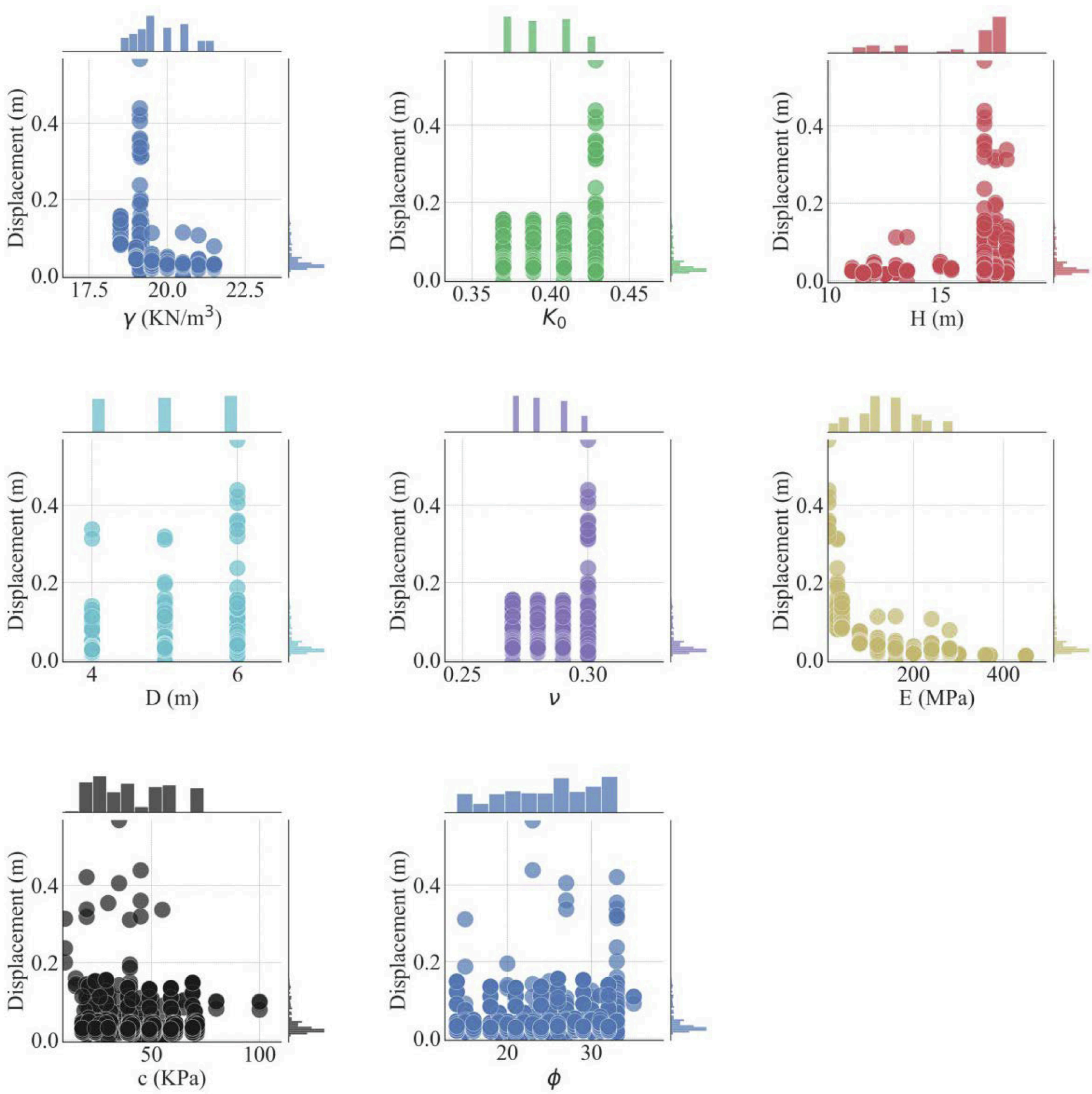

Fig. 4. Scatter plot of features in relation to output with marginal distribution.

square error (RMSE), and mean absolute error (MAE), are used to evaluate the agreement between the predicted values and the values calculated using FDM as illustrated in formulas 1–3. These indicators, which measure the variance, precision and absolute errors, ensure a thorough overall assessment of the model's predictive performance, and increase the reliability of the results.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(Dis - Dis_i^*\right)^2}{\sum_{i=1}^{n} \left(Dis_i^* - \overline{Dis}\right)^2} \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(Dis_i - Dis_i^*\right)^2} \tag{8}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left|Dis_i - Dis_i^*\right| \tag{9}$$

where n stands for the number of FDM data points, Dis_i is the predicted convergence displacement values, Dis_i^* stands for the FDM convergence displacement values, and $\overline{Dis}$ illustrates for the average convergence displacement.

Results and discussion

Best hyperparameters

In this study, five tree-based boosting ML algorithms were used to develop a model that can predict convergence displacement in shallow circular tunnels. The optimization of the hyperparameters for these models was performed using the Optuna package. In particular, the CMA-ES algorithm was used to fine-tune the hyperparameters. The dataset was split 80/20 between training and testing. The five algorithms analyzed were XGBoost, HGB, GBM, CatBoost and AdaBoost.

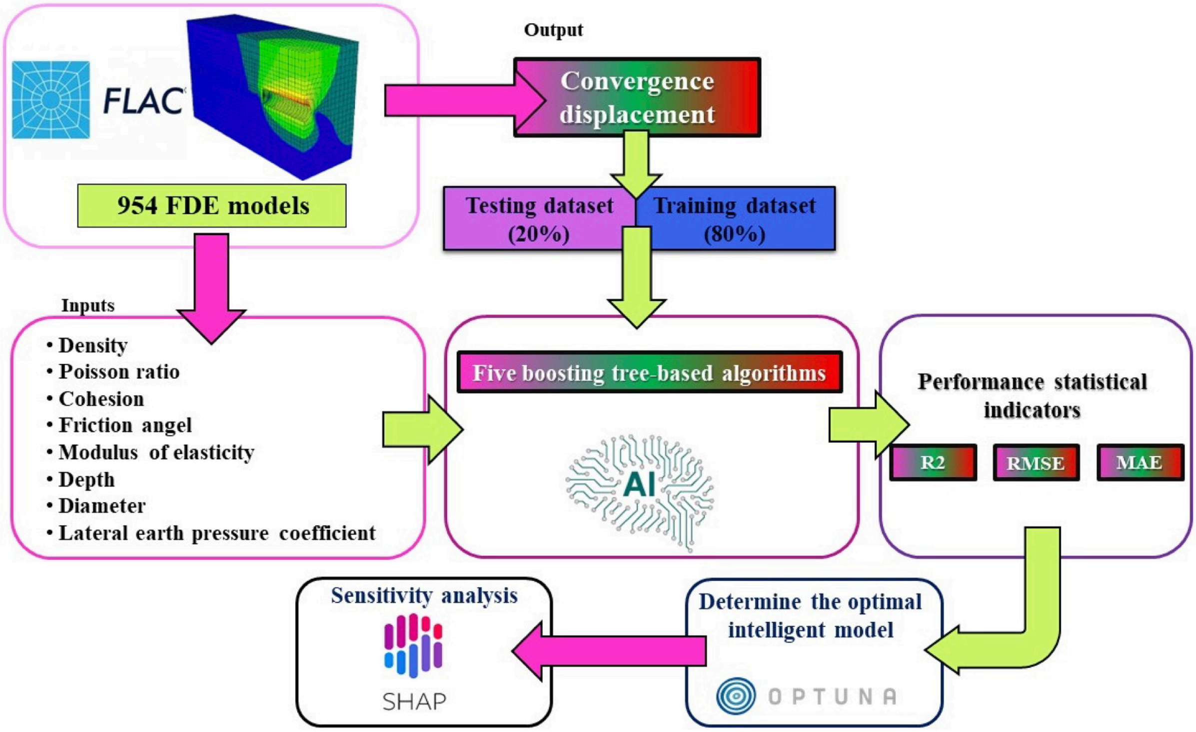

Fig. 5. Workflow describing the adopted approach.

Table 4
Tuned hyperparameters for the ML models.

Model	Hyperparameter	Value
XGBoost	n_estimators	184
	learning_rate	0.045
	max_depth	7
	min_child_weight	2
	subsample	0.809
	colsample_bytree	0.904
	gamma	9.18E-06
	reg_alpha	6.20E-06
	reg_lambda	0.1602
HGB	learning_rate	0.086
	max_iter	96
	max_depth	19
	min_samples_leaf	2
GBM	n_estimators	162
	learning_rate	0.116
	max_depth	6
	min_samples_split	0.040
	min_samples_leaf	0.017
	subsample	0.780
	max_features	0.902
	alpha	0.0001
CatBoost	n_estimators	143
	learning_rate	0.117
	depth	7
	min_child_samples	6
	subsample	0.745
	colsample_bylevel	0.654
	reg_lambda	0.0089
ADABoost	n_estimators	158
	learning_rate	0.016
	loss	exponential

These algorithms were evaluated based on their ability to accurately predict the convergence displacement and their computational efficiency. A summary of the fine-tuned hyperparameters for the five ML models is presented in Table 4.

Table 5
Assessment of the predictive performance of each model.

Algorithm	Dataset	R^2	MAE	RMSE	Execution time (s)
XGBoost	Train Set	0.9868	0.0015	3.55E-03	102.3
	Test Set	0.9633	0.0021	7.25E-03	
HGB	Train Set	0.9938	0.0009	2.43E-03	873.6
	Test Set	0.9608	0.002	7.48E-03	
GBM	Train Set	0.9774	0.0017	4.65E-03	207.2
	Test Set	0.9574	0.0023	7.80E-03	
CatBoost	Train Set	0.9968	0.0008	1.76E-03	242.9
	Test Set	0.9569	0.0022	7.85E-03	
AdaBoost	Train Set	0.9052	0.0066	9.53E-03	141.6
	Test Set	0.9030	0.0073	0.0117	

Assessment results

The outcomes of the five trained ML model assessments are presented in Table 5.

As shown in Table 5, among the evaluated ML algorithms for predicting the maximum convergence of shallow tunnels, XGBoost proves to be the top performer when comparing different metric measurements in the test dataset. XGBoost achieves the highest R^2 value of 0.9633, indicating an excellent degree of explained variance. Additionally, it showcases the lowest MAE value of 0.0021 and the lowest RMSE value of 7.25E-03, demonstrating its remarkable precision and consistency in predictions. HGB closely follows XGBoost in its performance, with a remarkable R^2 value of 0.9608, an MAE of 0.002, and an RMSE of 7.48E-03. GBM has strong predictive power for the test set with an R^2 of 0.9574, an MAE of 0.0023, and an RMSE of 7.80E-03. CatBoost also delivers respectable results on the test dataset, achieving an R^2 of 0.9569, an MAE of 0.0022, and an RMSE of 7.85E-03. Although AdaBoost has slightly lower performance on the test dataset, with an R^2 of 0.903, it still provides valuable insights, along with an MAE of 0.0073 and RMSE of 0.01. As a result, XGBoost performs excellently in predicting the maximum convergence of shallow tunnels, outperforming the other models on various metric measurements in the test dataset.

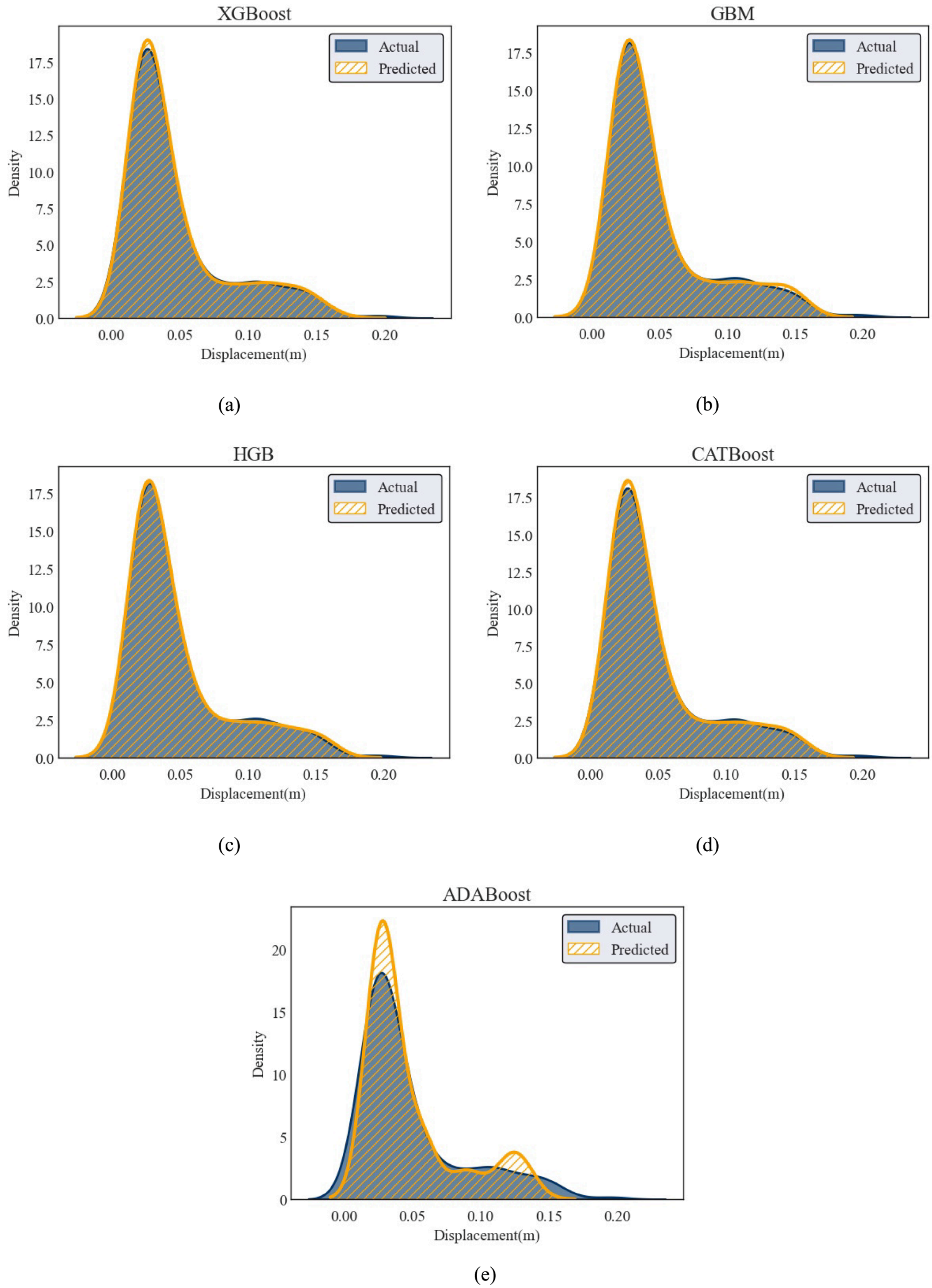

Fig. 6. Density distribution by using a) XGBoost, b) GBM, c) HGB, d) CatBoost, e) AdaBoostdisplacement for test dataset.

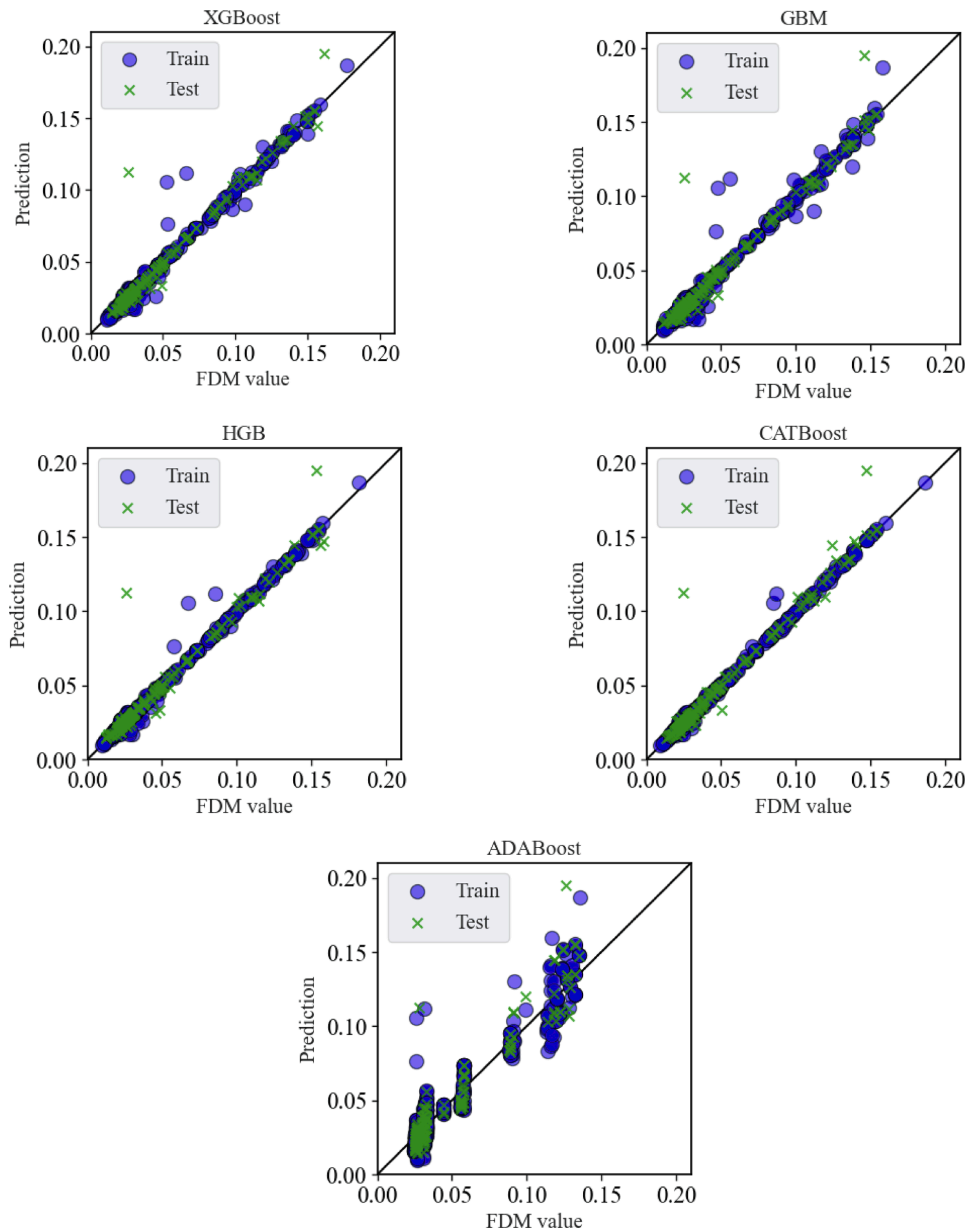

Fig. 7. Regression of the predicted versus the calculated convergence displacement of a tunnel using numerical method.

HGB, GBM, CatBoost, and AdaBoost also have acceptable performance levels, making them valuable alternatives for similar applications. When comparing the models based on execution time in Table 5, XGBoost shows the highest computational efficiency among the evaluated models with an execution time of 102.3 s for the training set. This is the shortest execution time compared to the other models, which are ranked in order of increasing execution time: AdaBoost (141.6 s), GBM (207.2 s), CatBoost (242.9 s) and HGB (873.6 s). These comparisons were performed on a computer equipped with an 11th Gen Intel(R) Core(TM) i9-11900H @ 2.50 GHz CPU and 16.0 GB DDR4 RAM. The analysis of the density distribution for the predicted displacement versus the actual displacement, calculated by FDM shows a high degree of agreement between the XGBoost, GBM, HGB, and CatBoost algorithms (Fig. 6). These models exhibit satisfactory coincidence between predicted values and FDM-calculated displacements. However, it is noteworthy that AdaBoost, exhibits slight discrepancies within the specific ranges of 0 to 0.05 and 0.1 to 0.2 m convergence Fig. 7 shows scatter plots depicting the predicted versus calculated convergence displacement of a tunnel using numerical method. The XGBoost regression model clearly outperforms the actual data within the tested displacement range, while the other algorithms fall just short of XGBoost.

Furthermore, Taylor diagrams were utilized to evaluate the standard deviation and correlation values between predicted and calculated convergence displacement values for the XGBoost, CatBoost, GBM, HGB, and AdaBoost models using different input parameters. Fig. 8 shows the Taylor diagrams for these models, with the distance from the reference point (shown as a black star) to each point indicating the centered RMSE. The model with the highest accuracy is therefore characterized by the smallest distance between the black star and the corresponding point. Specifically, for the test dataset, the XGBoost model, represented by a red dot, showed the most accurate predictions of the convergence displacement values for the shallow tunnel.

In our study, the Williams plot (Fig. 9) is used to evaluate the diagnostic robustness of the predictive modeling performed by the XGBoost algorithm. This plot allows a double assessment of leverage and standardized residuals and serves as an important visualization tool to

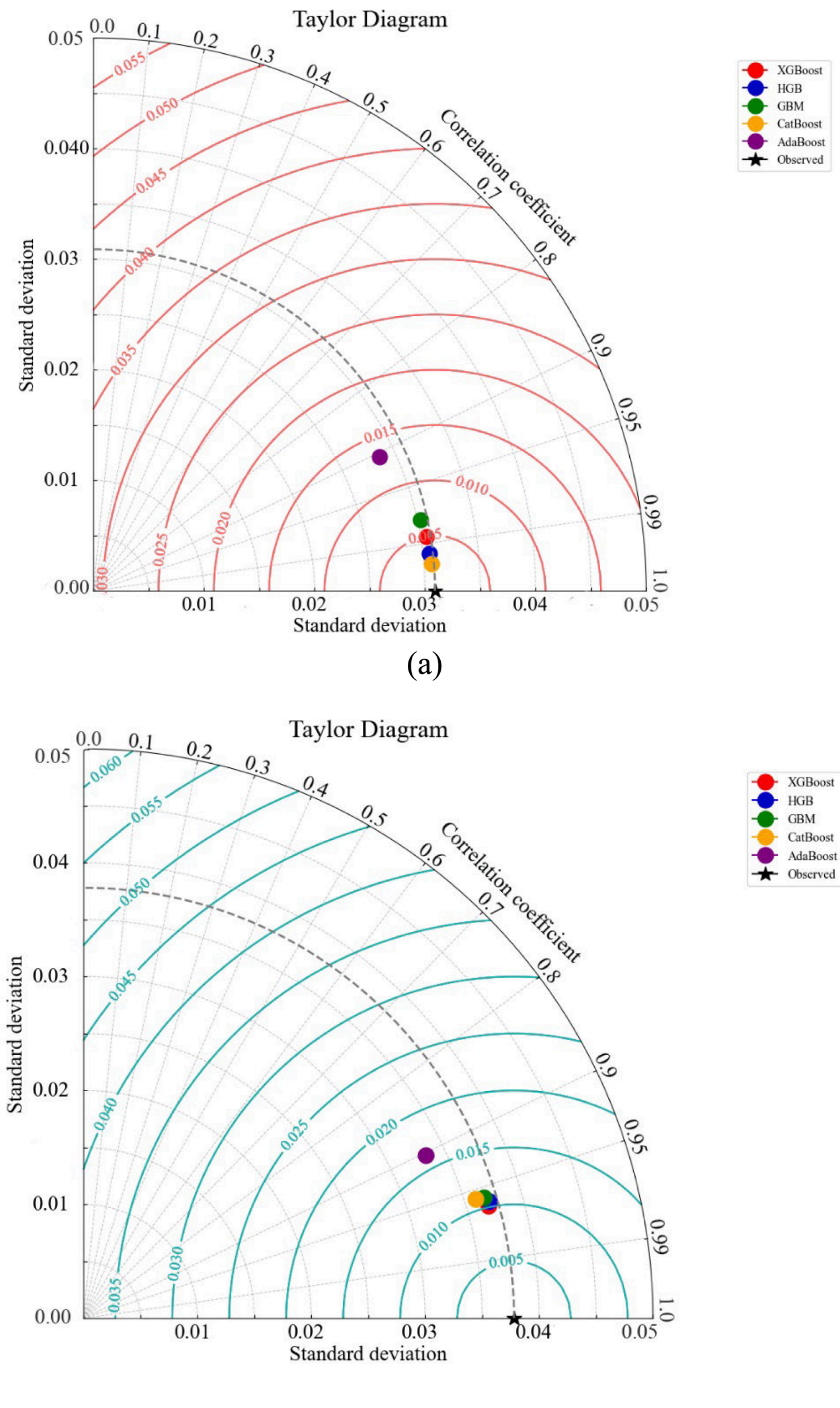

Fig. 8. Taylor diagram for all adopted algorithms, train dataset (a), test dataset (b).

investigate the influence and prediction error of individual observations within the dataset. In this context, leverage quantifies the potential influence of each data point on the parameter estimates of the model. High leverage points can excessively influence the model fit and are therefore of central importance for regression diagnostics. The leverage of each observation is plotted on the x-axis, with a higher value of leverage indicating a greater potential to influence the coefficients of the model. Standardized residuals represent the normalized differences between observed and predicted values and provide information about the prediction accuracy of the entire data set. These residuals are plotted on the

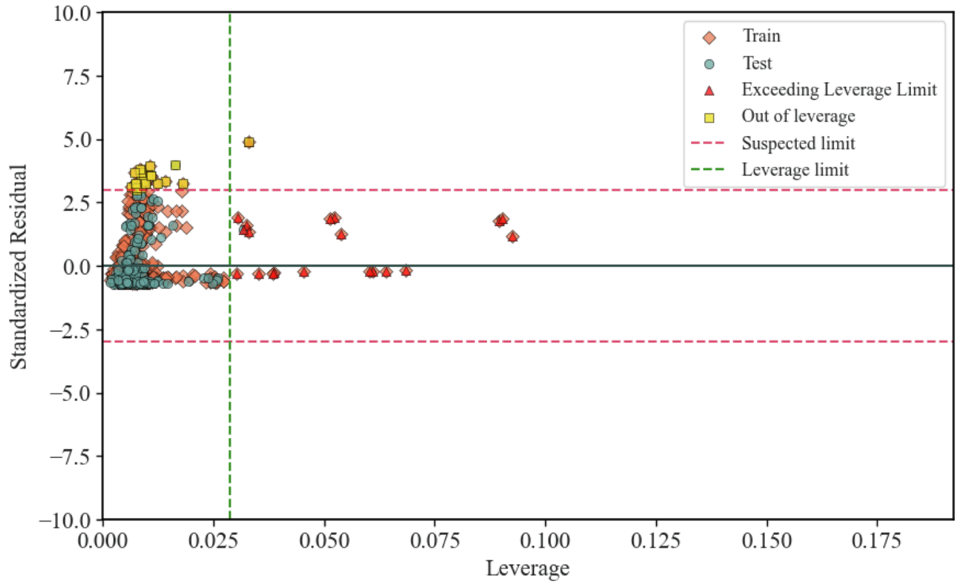

Fig. 9. Williams plot for XGBoost model.

y-axis, with values close to zero indicating a strong agreement between predicted and observed results and deviations beyond the threshold values of ± 3 indicating possible outliers or inadequacies of the model. The graph delineates the range of application, which is defined by fixed thresholds for both the leverage effect and the residuals. In our analysis, a significant majority of data points for both the training sample (94.53 %) and the test sample (98.94 %) are within this range, highlighting the efficiency and stability of the model. Such positioning within the graph suggests that the model predictions are both reliable and robust, closely adhering to the observed data behavior. To improve the clarity and usefulness of the Williams diagram, we have included color-coded markers and reference lines:

- Color-coded markers distinguish between data points that adhere to expected behavior and those that are outliers or could exert undue influence.
- Reference lines are strategically placed at the leverage and residual thresholds to visually reinforce these critical boundaries, allowing for quick identification of data points that warrant further investigation.

This visualization not only confirms the XGBoost model's ability to capture essential data patterns, but also highlights its precision in dealing with different data observations and validating its application to new data sets. The comprehensive assessment of the model diagnosis by the Williams plot is an essential part of our analysis and ensures that the model operates within a well-defined and scientifically justified framework.

Fig. 10a and Fig. 11a illustrate a comparison between the tunnel convergence displacement obtained from the proposed XGBoost model and the actual numerical data during the training and testing process. Overall, there is a notable concordance between the two datasets. In Fig. 10b and Fig. 11b, the evolution of the error with respect to the variation of the number of samples. In addition, Fig. 10c and Fig. 11c display a histogram representing the distribution of error values during training. It is obvious that the majority of errors during the training process are closely clustered around 0. A similar trend can be observed when the results of the XGBoost model are compared with the corresponding numerical data for the test dataset.

Feature importance

XGBoost feature importance

The feature importance of the XGBoost is a critical aspect of the algorithm that quantifies the contribution of each feature to the predictive performance of the model. By analyzing the importance scores, practitioners gain valuable insight into the relative influence of features, which facilitates informed decisions about feature selection, model interpretation, and optimization for improved prediction accuracy. In Fig. 12 the feature importance analysis shows that the most influential factors contributing to the maximum convergence displacement, our target variable, are the modulus of elasticity with a significance of 0.646, followed by the unit weight of soil with 0.174. The depth of the tunnel also plays a notable role, albeit to a lesser extent, with a significance factor of 0.065. Other parameters such as the tunnel diameter, the cohesion, the earth pressure coefficient at rest and the friction angle show varying degrees of importance with 0.039, 0.027, 0.018, and 0.017, respectively. In addition, the Poisson's ratio is a factor with an importance factor of 0.014, but it has relatively little influence. This comprehensive analysis provides valuable insight into the relative importance of each parameter in influencing the maximum convergence displacement, which contributes to the understanding and possible optimization of tunneling or excavation processes to improve structural stability.

SHAP evaluation

In recent years, the SHAP (SHapley Additive exPlanations) technique has been widely applied in various engineering disciplines and provides valuable insights into the interpretability of predictive models [4,6,12,19,21,30,34]. In this research, a detailed assessment of feature importance is conducted using SHAP values, offering valuable insight into the relative importance of each feature in predicting the maximum convergence of shallow tunnels (Fig. 13). The analysis clearly shows that the modulus of elasticity has the largest and most variable influence on the model's predictions. The large scatter of SHAP values for this parameter shows that the stiffness of the material is a decisive factor for the convergence behavior of the tunnel structure, with higher stiffness correlating with lower displacement. The graph also illustrates the essential role of other geotechnical properties such as the depth of the tunnel and the cohesion of the soil. Both show a scatter of positive SHAP values, which means that their increased presence can potentially contribute to a reduction in displacement, indicating a stabilizing effect

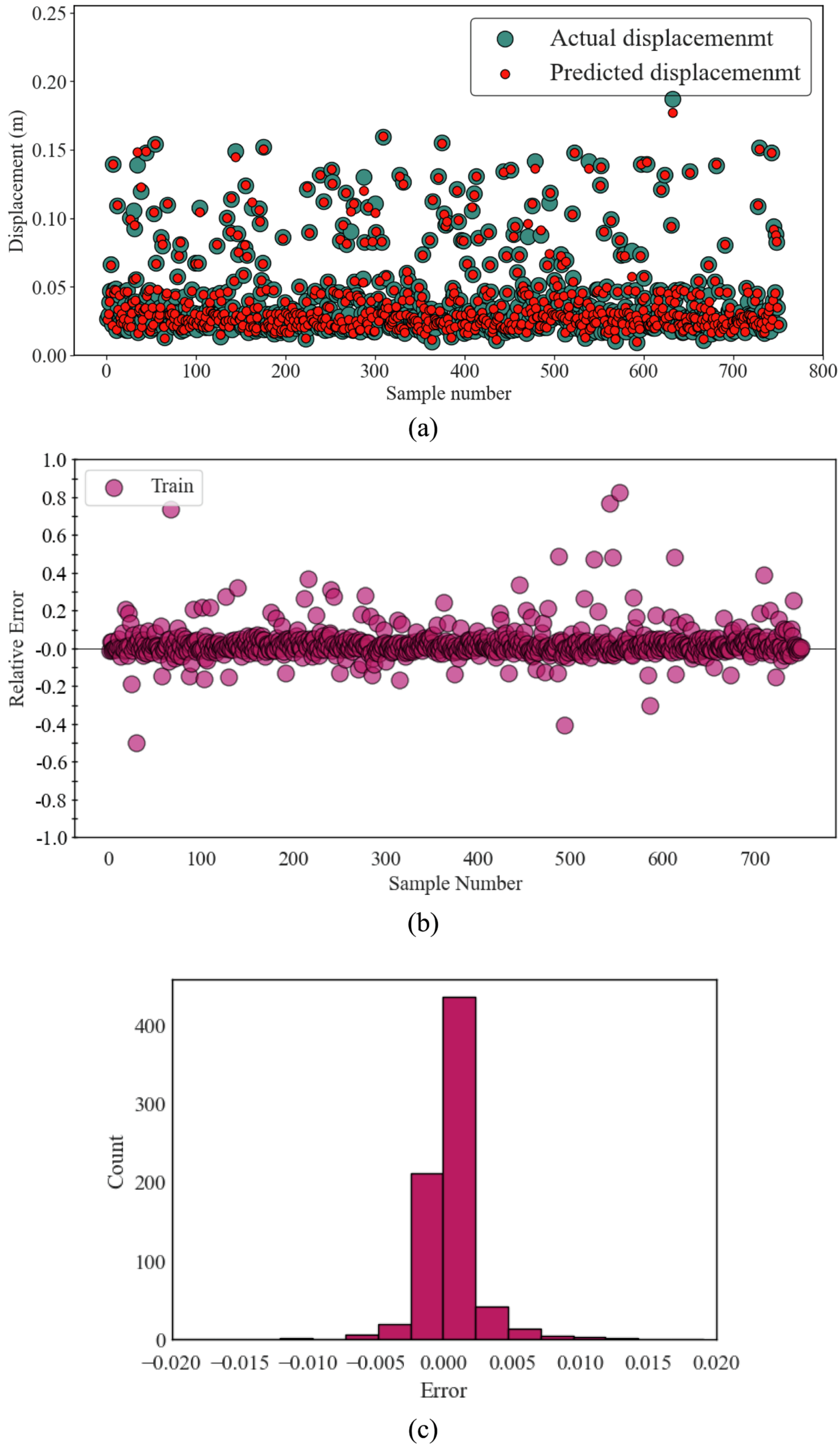

Fig. 10. (a) Assessment of the accuracy of convergence displacement predictions generated by the XGBoost model, (b) relative error, (c) distribution of residual error (Train samples).

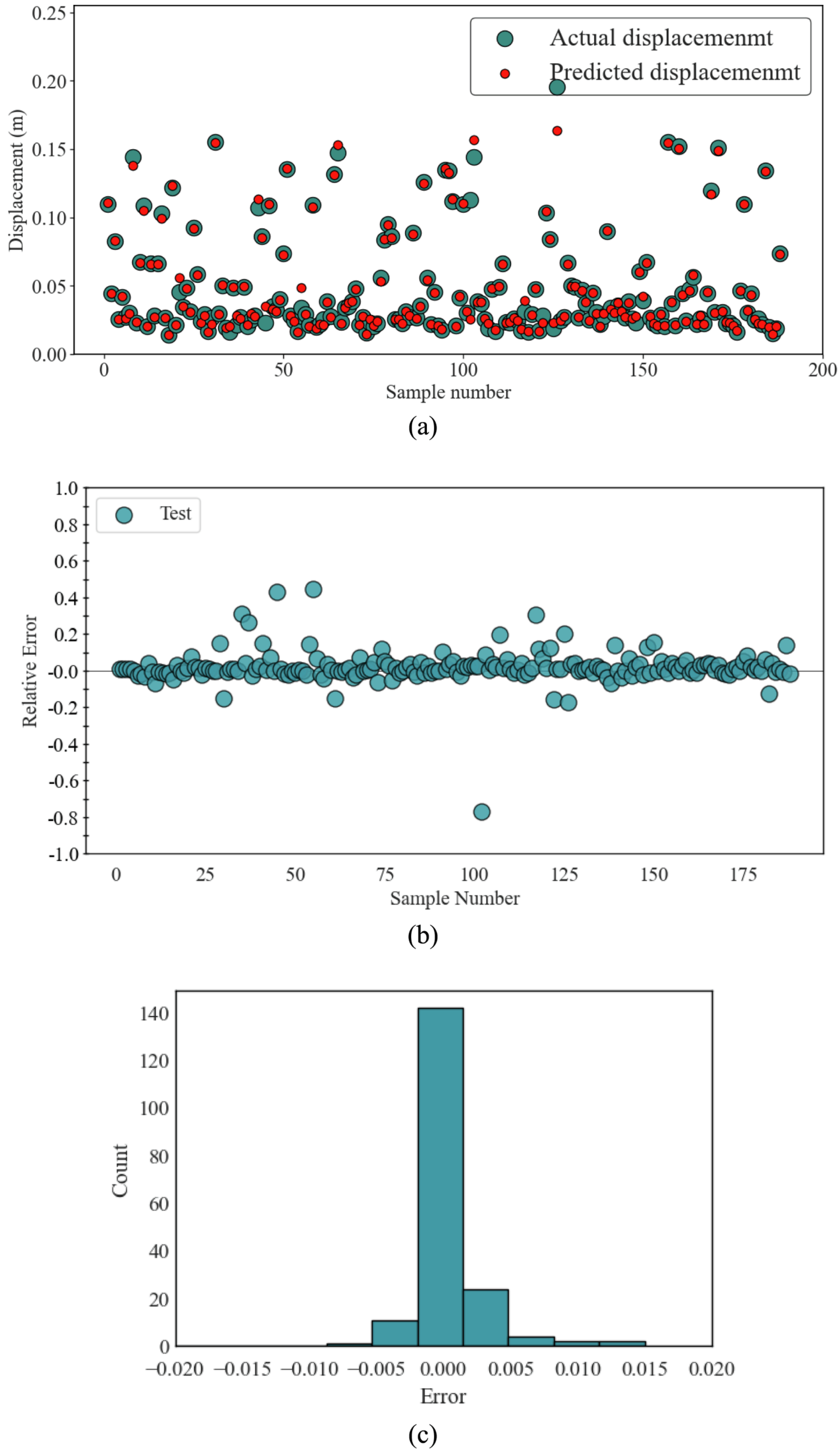

Fig. 11. (a) Assessment of the accuracy of convergence displacement predictions generated by the XGBoost model, (b) relative error, (c) distribution of residual error (Test samples).

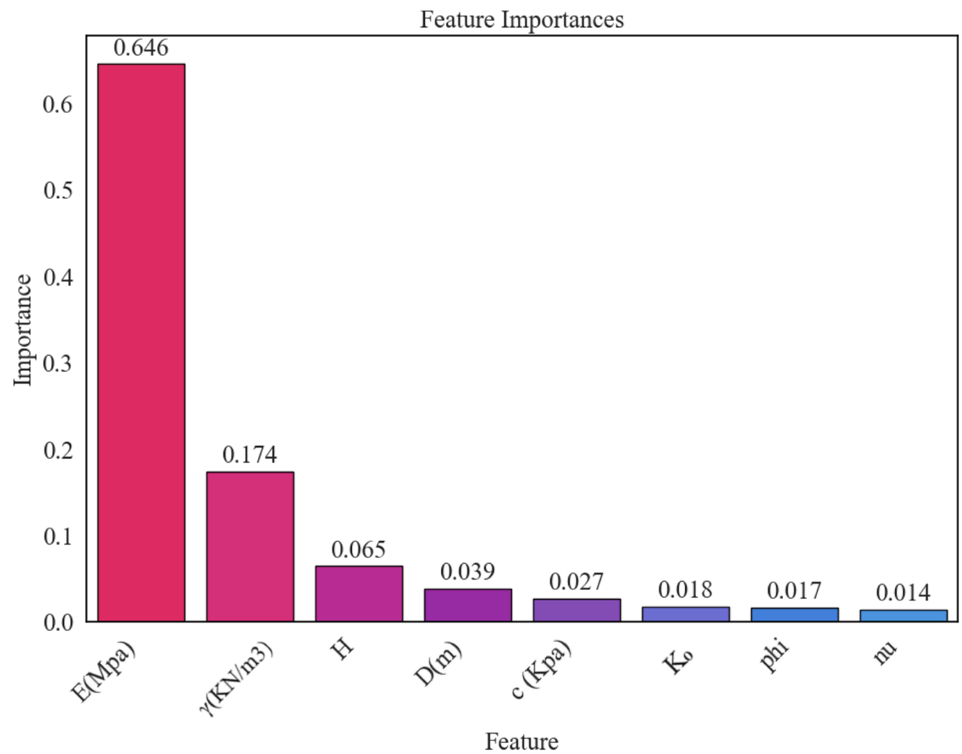

Fig. 12. XGBoost feature importance.

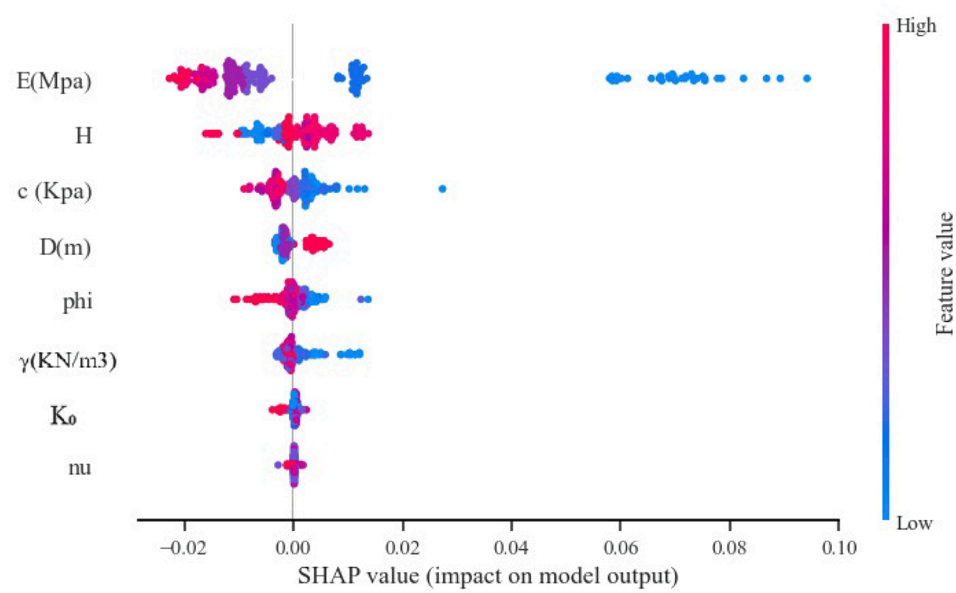

Fig. 13. SHAP values for XGBoost model.

on the tunnel structure. In contrast, the angle of internal friction, unit weight and coefficient of earth pressure at rest have SHAP values that cluster around the baseline, indicating a less pronounced but still complicated relationship with the displacement result. This complexity could reflect the different nature of the geological formations and their response under stress. While Poisson's ratio is not as influential as modulus of elasticity or height, it still exhibits a recognizable clustering of SHAP values. This closer clustering near the baseline indicates a more consistent influence across different instances of the dataset. In summary, the SHAP analysis underscores the paramount importance of the modulus of elasticity in predicting the convergence displacement of the tunnel, with other parameters governing the mechanical behavior of earth materials also making a notable contribution. The findings from this model are of great importance for structural engineering considerations, both for planning and for preventive measures in tunnel construction.

Feature importance conclusion

In conclusion, the combined analysis of SHAP values and XGBoost feature importance provides a comprehensive understanding of the most important factors influencing the predictive model for the maximum convergence displacement. The modulus of elasticity proves to be a key feature and emphasizes its crucial contribution to the overall performance of the model. The unit weight of the soil follows closely behind and emphasizes its significant influence. In addition, the depth of the tunnel, tunnel diameter, cohesion, earth pressure coefficient at rest, and friction angle all contribute to varying degrees and provide a nuanced insight into their respective roles. This holistic assessment provides practitioners with valuable information for informed decision-making in feature selection, model interpretation, and optimization, and ultimately improves the accuracy of maximum convergence displacement prediction.

Conclusion

This study focused on the prediction of convergence displacement in unsupported shallow tunnels by creating and analyzing a database of 954 data points. This dataset was carefully compiled using FLAC 3D software and FDM, with particular attention paid to the selection of significant features as model inputs. To predict the convergence displacement, the study utilized the performance of five tree-based boosting algorithms: XGBoost, ADABoost, GBM, HGB and CatBoost. The precision and stability of these models were evaluated using statistical indicators and visual analysis. In addition, a detailed sensitivity analysis was performed considering XGBoost feature importance and SHAP values to identify the most important factors for the most effective intelligent model. The key findings are described below:

- A robust database of 954 samples, carefully constructed with verified data from FDM simulations and verified with empirical formulas, comprehensively accounts for crucial features that influence the maximum convergence displacement. This rigorous approach increases the credibility and reliability of the predictive models. An advanced intelligent framework is presented that provides a method for reducing the costs associated with the complexity, expense, and time involved in numerical modeling.
- XGBoost, harnessing the boosting technique for weak learners, proves to be the most effective algorithm for predicting convergence in shallow tunnels among the others. Overall, the algorithms using boosting techniques show a strong ability to accurately predict the convergence displacement of shallow tunnels.
- The predictions agree exactly with the displacements calculated by FDM for several models: XGBoost achieved an impressive R^2 of 0.9633, with an MAE of 0.0021 and an RMSE of 0.00725. GBM, HGB and CatBoost also performed well, with R^2 values of 0.9574, 0.9608 and 0.9569, respectively, and corresponding MAE and RMSE values. This comparison underlines the accuracy and reliability of the prediction models. Different assessments and Taylor diagram evaluations confirm the accuracy of XGBoost in replicating the actual data.
- The modulus of elasticity proves to be a decisive feature that influences the maximum convergence displacement in a shallow circular tunnel.

In conclusion, our study emphasizes the effectiveness of XGBoost in predicting convergence displacement in shallow tunnels. The model's accuracy and robust behavior, as indicated by various evaluations, highlight its reliability for practical applications. These findings contribute to advancing our understanding of tunneling behavior and offer valuable insights for optimizing predictive models in tunneling process. In addition, this research equips geotechnical engineers with improved predictive tools for underground construction by using ML for more accurate assessments of structural behavior. It enables more reliable and cost-efficient project planning and advances geotechnical engineering by improving the safety and efficiency of tackling underground challenges.

CRediT authorship contribution statement

Danial Sheini Dashtgoli: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rasool Sadeghian:** Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation, Conceptualization. **Ahmad Reza Mahboubi Ardakani:** Writing – review & editing, Validation, Supervision, Investigation. **Hamid Mohammadnezhad:** Writing – original draft, Validation, Supervision, Investigation. **Michela Giustiniani:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Investigation, Conceptualization. **Martina Busetti:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Investigation, Conceptualization. **Claudia Cherubini:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

[1] Akiba, T., Sano, S., Yanase, T., Ohta, T., & Koyama, M. (2019). Optuna: A Next-generation Hyperparameter Optimization Framework. *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2623–2631. Doi: 10.1145/3292500.3330701.

[2] Alejano LR, Rodríguez-Dono A, Veiga M. Plastic radii and longitudinal deformation profiles of tunnels excavated in strain-softening rock masses. Tunn Undergr Space Technol 2012;30:169–82. https://doi.org/10.1016/j.tust.2012.02.017.

[3] Basarir H, Genis M, Ozarslan A. The analysis of radial displacements occurring near the face of a circular opening in weak rock mass. Int J Rock Mech Min Sci 2010;47 (5):771–83. https://doi.org/10.1016/j.ijrmms.2010.03.010.

[4] Bekdaş G, Cakiroglu C, Kim S, Geem ZW. Optimal dimensions of post-tensioned concrete cylindrical walls using harmony search and ensemble learning with SHAP. Sustainability 2023;15(10):7890. https://doi.org/10.3390/su15107890.

[5] Bourel M, Segura AM, Crisci C, López G, Sampognaro L, Vidal V, et al. Machine learning methods for imbalanced data set for prediction of faecal contamination in beach waters. Water Res 2021;202:117450. https://doi.org/10.1016/j.watres.2021.117450.

[6] Cakiroglu C, Islam K, Bekdaş G, Isikdag U, Mangalathu S. Explainable machine learning models for predicting the axial compression capacity of concrete filled steel tubular columns. Constr Build Mater 2022;356:129227. https://doi.org/10.1016/j.conbuildmat.2022.129227.

[7] Carranza-Torres C, Fairhurst C. Application of the Convergence-Confinement method of tunnel design to rock masses that satisfy the Hoek-Brown failure criterion. Tunn Undergr Space Technol 2000;15(2):187–213. https://doi.org/10.1016/S0886-7798(00)00046-8.

[8] Chang X, Wang H, Zhang Y, Wang F, Li Z. Bayesian prediction of tunnel convergence combining empirical model and relevance vector machine. Measurement 2022;188:110621. https://doi.org/10.1016/j.measurement.2021.110621.

[9] Chen, T., & Guestrin, C. (2016). *XGBoost: A Scalable Tree Boosting System*. Doi: 10.48550/ARXIV.1603.02754.

[10] Dorogush, A. V., Ershov, V., & Gulin, A. (2018). *CatBoost: Gradient boosting with categorical features support*. Doi: 10.48550/ARXIV.1810.11363.

[11] Fathipour-Azar H. Multi-level machine learning-driven tunnel squeezing prediction: Review and new insights. Arch Comput Meth Eng 2022;29(7):5493–509. https://doi.org/10.1007/s11831-022-09774-z.

[12] Feng D-C, Wang W-J, Mangalathu S, Taciroglu E. Interpretable XGBoost-SHAP machine-learning model for shear strength prediction of squat RC walls. J Struct Eng 2021;147(11):04021173. https://doi.org/10.1061/(ASCE)ST.1943-541X.0003115.

[13] Freund Y, Schapire RE. A decision-theoretic generalization of on-line learning and an application to boosting. J Comput Syst Sci 1997;55(1):119–39. https://doi.org/10.1006/jcss.1997.1504.

[14] Friedman JH. Greedy function approximation: A gradient boosting machine. Ann Stat 2001:1189–232.

[15] Geng X, Wu S, Zhang Y, Sun J, Cheng H, Zhang Z, et al. Developing hybrid XGBoost model integrated with entropy weight and Bayesian optimization for predicting

tunnel squeezing intensity. Nat Hazards 2023;119(1):751–71. https://doi.org/10.1007/s11069-023-06137-0.
[16] Hansen, N. (2016). *The CMA Evolution Strategy: A Tutorial*. Doi: 10.48550/ARXIV.1604.00772.
[17] Hoek, E. (2018). Support for very weak rock associated with faults and shear zones. In *Rock support and reinforcement practice in mining* (pp. 19–32). Routledge.
[18] Li J-B, Chen Z-Y, Li X, Jing L-J, Zhangf Y-P, Xiao H-H, et al. Feedback on a shared big dataset for intelligent TBM Part I: Feature extraction and machine learning methods. Undergr Space 2023;11:1–25. https://doi.org/10.1016/j.undsp.2023.01.001.
[19] Liu T, Cakiroglu C, Islam K, Wang Z, Nehdi ML. Explainable machine learning model for predicting punching shear strength of FRC flat slabs. Eng Struct 2024;301:117276. https://doi.org/10.1016/j.engstruct.2023.117276.
[20] Lundberg, S. M., Erion, G. G., & Lee, S.-I. (2018). *Consistent Individualized Feature Attribution for Tree Ensembles*. Doi: 10.48550/ARXIV.1802.03888.
[21] Mangalathu S, Hwang S-H, Jeon J-S. Failure mode and effects analysis of RC members based on machine-learning-based SHapley Additive exPlanations (SHAP) approach. Eng Struct 2020;219:110927. https://doi.org/10.1016/j.engstruct.2020.110927.
[22] Nam S-W, Bobet A. Radial deformations induced by groundwater flow on deep circular tunnels. Rock Mech Rock Eng 2007;40(1):23–39. https://doi.org/10.1007/s00603-006-0097-4.
[23] Paraskevopoulou C, Diederichs M. Analysis of time-dependent deformation in tunnels using the Convergence-Confinement Method. Tunn Undergr Space Technol 2018;71:62–80. https://doi.org/10.1016/j.tust.2017.07.001.
[24] Prassetyo SH, Gutierrez M. Effect of transient coupled hydro-mechanical response on the longitudinal displacement profile of deep tunnels in saturated ground. Tunn Undergr Space Technol 2018;75:11–20. https://doi.org/10.1016/j.tust.2018.02.003.
[25] Sadeghiyan R, Hashemi M, Moloudi E. Determination of longitudinal convergence profile considering effect of soil strength parameters. Int J Rock Mech Min Sci 2016;82:10–21. https://doi.org/10.1016/j.ijrmms.2015.10.011.
[26] Shan F, He X, Xu H, Armaghani DJ, Sheng D. Applications of machine learning in mechanised tunnel construction: A systematic review. Eng 2023;4(2):1516–35. https://doi.org/10.3390/eng4020087.
[27] Sheini Dashtgoli D, Dehnad MH, Mobinipour SA, Giustiniani M. Performance comparison of machine learning algorithms for maximum displacement prediction in soldier pile wall excavation. Undergr Space 2024;16:301–13. https://doi.org/10.1016/j.undsp.2023.09.013.
[28] Shin Y-J, Kim D-H, Lee I-M. Numerical simulation of seepage-induced behavior of tunnel for analyzing deformation characteristic and estimating geotechnical parameters. KSCE J Civ Eng 2014;18(2):659–71. https://doi.org/10.1007/s12205-014-0466-6.
[29] Vlachopoulos N, Diederichs MS. Improved longitudinal displacement profiles for convergence confinement analysis of deep tunnels. Rock Mech Rock Eng 2009;42(2):131–46. https://doi.org/10.1007/s00603-009-0176-4.
[30] Wakjira TG, Ibrahim M, Ebead U, Alam MS. Explainable machine learning model and reliability analysis for flexural capacity prediction of RC beams strengthened in flexure with FRCM. Eng Struct 2022;255:113903. https://doi.org/10.1016/j.engstruct.2022.113903.
[31] Wang H, Liu E, Wei H. Tunnel boring machine performance assessment and prediction applying hybrid artificial intelligence. J Intell Fuzzy Syst 2023;1–18. https://doi.org/10.3233/JIFS-232989.
[32] Wang J, Mohammed AS, Macioszek E, Ali M, Ulrikh DV, Fang Q. A novel combination of PCA and machine learning techniques to select the most important factors for predicting tunnel construction performance. Buildings 2022;12(7):919. https://doi.org/10.3390/buildings12070919.
[33] Wang, R., Chen, G., & Liu, Y. (2023). A Dynamic Model of Machine Learning and Deep Learning in Shield Tunneling Parameters Prediction. In G. Geng, X. Qian, L. H. Poh, & S. D. Pang (Eds.), *Proceedings of The 17th East Asian-Pacific Conference on Structural Engineering and Construction, 2022* (Vol. 302, pp. 1241–1254). Springer Nature Singapore. Doi: 10.1007/978-981-19-7331-4_99.
[34] Zarringol, M., & Naser, M. Z. (2024). Explainable machine learning model for prediction of axial capacity of strengthened CFST columns. In *Interpretable Machine Learning for the Analysis, Design, Assessment, and Informed Decision Making for Civil Infrastructure* (pp. 229–253). Elsevier. Doi: 10.1016/B978-0-12-824073-1.00016-2.
[35] Zhou J, Chen Y, Li C, Qiu Y, Huang S, Tao M. Machine learning models to predict the tunnel wall convergence. Transp Geotech 2023;41:101022. https://doi.org/10.1016/j.trgeo.2023.101022.