

In-depth exploration of machine learning algorithms for predicting sidewall displacement in underground caverns

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Abstract. This paper delves into the critical assessment of predicting sidewall displacement in underground caverns through the application of nine distinct machine learning techniques. The accurate prediction of sidewall displacement is essential for ensuring the structural safety and stability of underground caverns, which are prone to various geological challenges. The dataset utilized in this study comprises a total of 310 data points, each containing 13 relevant parameters extracted from 10 underground cavern projects located in Iran and other regions. To facilitate a comprehensive evaluation, the dataset is evenly divided into training and testing subset. The study employs a diverse array of machine learning models, including recurrent neural network, back-propagation neural network, K-nearest neighbors, normalized and ordinary radial basis function, support vector machine, weight estimation, feed-forward stepwise regression, and fuzzy inference system. These models are leveraged to develop predictive models that can accurately forecast sidewall displacement in underground caverns. The training phase involves utilizing 80% of the dataset (248 data points) to train the models, while the remaining 20% (62 data points) are used for testing and validation purposes. The findings of the study highlight the back-propagation neural network (BPNN) model as the most effective in providing accurate predictions. The BPNN model demonstrates a remarkably high correlation coefficient ($R^2 = 0.99$) and a low error rate ($RMSE = 4.27E-05$), indicating its superior performance in predicting sidewall displacement in underground caverns. This research contributes valuable insights into the application of machine learning techniques for enhancing the safety and stability of underground structures.

Keywords: importance ranking; machine learning algorithms; sidewall displacement; underground caverns

1. Introduction

Subsurface projects like tunnels and caverns stand as pivotal engineering ventures, their necessity burgeoning with each passing day (Hu *et al.* 2023, Liu *et al.* 2021, Su *et al.* 2023a, Wei *et al.* 2023). Yet, inherent to such undertakings are manifold hazards and mishaps that can yield devastating financial and human tolls. Hence, meticulous scrutiny, prognostication, and the formulation of apt remedies are imperative to mitigate such perils.

Of paramount concern is the structural integrity of underground caverns, for any negligence in this regard could precipitate catastrophic collapses. Therefore, a dedicated focus on studying, forecasting, and implementing robust solutions becomes indispensable.

Given their significant importance, there has been a global increase in the construction of underground caverns, particularly in developed countries (Zhang and Goh 2012, 2015).

These colossal edifices fulfill diverse functions, from

sheltering turbines, electrical generators, and transformers in hydroelectric endeavors to acting as repositories for liquid or gaseous fuels, subterranean storehouses, and venues for sporting events. Given their monumental scale, constructing them entails myriad risks, spanning structural integrity, stability, and the temporal and financial investments involved. Particularly, the lateral displacement of cavern walls emerges as a paramount apprehension, for early detection thereof enables the deployment of apt remedies to alleviate the perils inherent in construction endeavors (Zhang and Goh 2013).

In the existing literature, various approaches have been employed to forecast displacement in underground spaces, including empirical, numerical, and theoretical models. Numerical methods, in particular, are commonly utilized for estimating displacements. However, there is currently no straightforward method for predicting displacements, as numerical models developed for specific cases may not be applicable to other cases. Furthermore, empirical models may only cover the identification of maximal displacement using certain parameters. Consequently, new approaches, such as smart predictor networks and intelligence computational techniques, are needed to adequately address the demand for sidewall displacement prediction in

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underground caverns. Therefore, this paper aims to propose machine learning (ML) models for predicting sidewall displacement of underground caverns (Zhu *et al.* 2010, Li *et al.* 2022).

Recent developments have led to the use of smart predictor networks based on ML and deep learning (DL) algorithms to analyze geotechnical issues (Zhang and Goh 2013, Rajabi *et al.* 2017). ML methods, in particular, can learn non-linear functional mappings and are capable of handling complex functions. Previous researchers have successfully applied ML methods to address tunneling issues and geotechnical problems (Chou *et al.* 2016, Zhang and Goh 2016, Pham *et al.* 2018, Puri *et al.* 2018). These algorithms enable computers to learn from data and make predictions or decisions without being explicitly programmed for each task (Lei *et al.* 2024, Shi *et al.* 2023a, b, Su *et al.* 2023b, Yin *et al.* 2023). However, the potential of ML methods to accurately predict sidewall displacement of caverns has not been thoroughly investigated, with only a few studies exploring the use of artificial neural networks (ANNs) to predict sidewall displacement in power station caverns (Abdollahipour and Rahmancejad 2013, Rajabi *et al.* 2017).

ML techniques represent a recent technological advancement in addressing engineering and scientific challenges, demonstrating significant potential in the estimation and prediction of various engineering problems (Samadi *et al.* 2022, Kamran *et al.* 2022, Mahmoodzadeh *et al.* 2022 a, b, Lawal *et al.* 2023, Abdelmawla *et al.* 2023, Samadi *et al.* 2023, Khatti *et al.* 2023, Albaijan *et al.* 2024).

Within this context, the analysis of sidewall displacement of underground caverns has greatly benefited from the application of cutting-edge technologies such as artificial intelligence (AI) and ML (Shahmohammadi *et al.* 2020, Zhang *et al.* 2020a). The precision and predictive capabilities of these models aim to provide accurate assessments of sidewall displacement, utilizing algorithms that learn from previous data examples and apply that knowledge to new situations. Both deep learning and shallow algorithms are employed in ML, with the accuracy of predictions directly influenced by the learning rate and type of learning paradigm, such as unsupervised, supervised, or reinforcement learning (Zhang *et al.* 2020 (b); Wang *et al.* 2020).

The motivation behind the application of ML methods in generating Sidewall Displacement for Underground Caverns is threefold. Firstly, providing accurate estimations of sidewall displacement is crucial for ensuring the safety and stability of underground caverns, a task which is often hindered by high error rates when using conventional methods that rely on simplified assessments and specific assumptions (Zhu *et al.* 2008, Zhu *et al.* 2010a). Secondly, uncertainties inherent in the assessment procedure of sidewall displacement can limit the accuracy of estimates, a challenge which ML can effectively address through its ability to account for such ambiguities and enhance performance through the learning process. Finally, the assessment and dependability of machine learning models, facilitated by fundamental pillars of ML analysis like the confusion matrix, evaluation metrics, and loss function,

assume pivotal significance in decision-making and the deployment of stabilizing methodologies. They enable meticulous measurement and appraisal of the efficacy of learning models, empowering the implementation of informed strategies (Zhu *et al.* 2010, Goh *et al.* 2018).

Given the inherent uncertainty in geotechnical engineering and underground construction applications, ML approaches offer an effective means of constructing robust prediction models for sidewall displacement and anticipating and stabilizing crucial parameters. The ongoing research aims to forge precise models for predicting sidewall displacement in subterranean caverns employing a range of prevalent machine learning techniques. Its objective is to confront the hurdles presented by the erratic nature and diverse facets of factors like cavern geometry, geologic material attributes, and strength properties.

This research recognizes the power of ML processes in providing more capable and efficient methods to accurately assess and predict sidewall displacement in underground caverns (Zhang *et al.* 2020a, Wang *et al.* 2020). The present study diligently employed multiple ubiquitous machine learning methods to craft precise models aimed at estimating sidewall displacement in underground cavern. Numerous potential main analytic cores, including recurrent neural network (RNN), back-propagation neural networks (BPNN), K-nearest neighbors (KNN), normalized and ordinary radial basis functions (NRBF-ORBF), support vector machine (SVM), weight estimation (WE), feed-forward stepwise regression (FFSR), and fuzzy inference system (FIS), were evaluated in this study. These algorithms have gained widespread adoption in academic circles, particularly within the geotechnical and underground construction analysis domains, due to their exceptional attributes and various advantages. Notable benefits of these algorithms include;

- their ability to process both linear and nonlinear data for regression and classification purposes;
- their effectiveness in distinguishing between different groups using decision boundaries;
- their facilitation of capability and error calculations through careful consideration of options and cost weighing;
- their significant reduction of computation time and adaptability to varying complexity of study;
- their ability to enable more precise estimations and reduce errors;
- their accessibility and efficiency.

Unveiling these models holds the promise of dispelling existing uncertainties surrounding sidewall displacement, thereby propelling forward the application of machine learning techniques in the domain. Such unveiling could lay down a robust groundwork for future advancements, reshaping the paradigm concerning sidewall displacement in underground caverns and elevating safety protocols. A schematic representation outlining the progression of the proposed research is delineated in Fig. 1.

The study utilized a dataset containing 310 entries with 12 parameters influencing sidewall displacement, with 80% of the data allocated for training and 20% for validation.

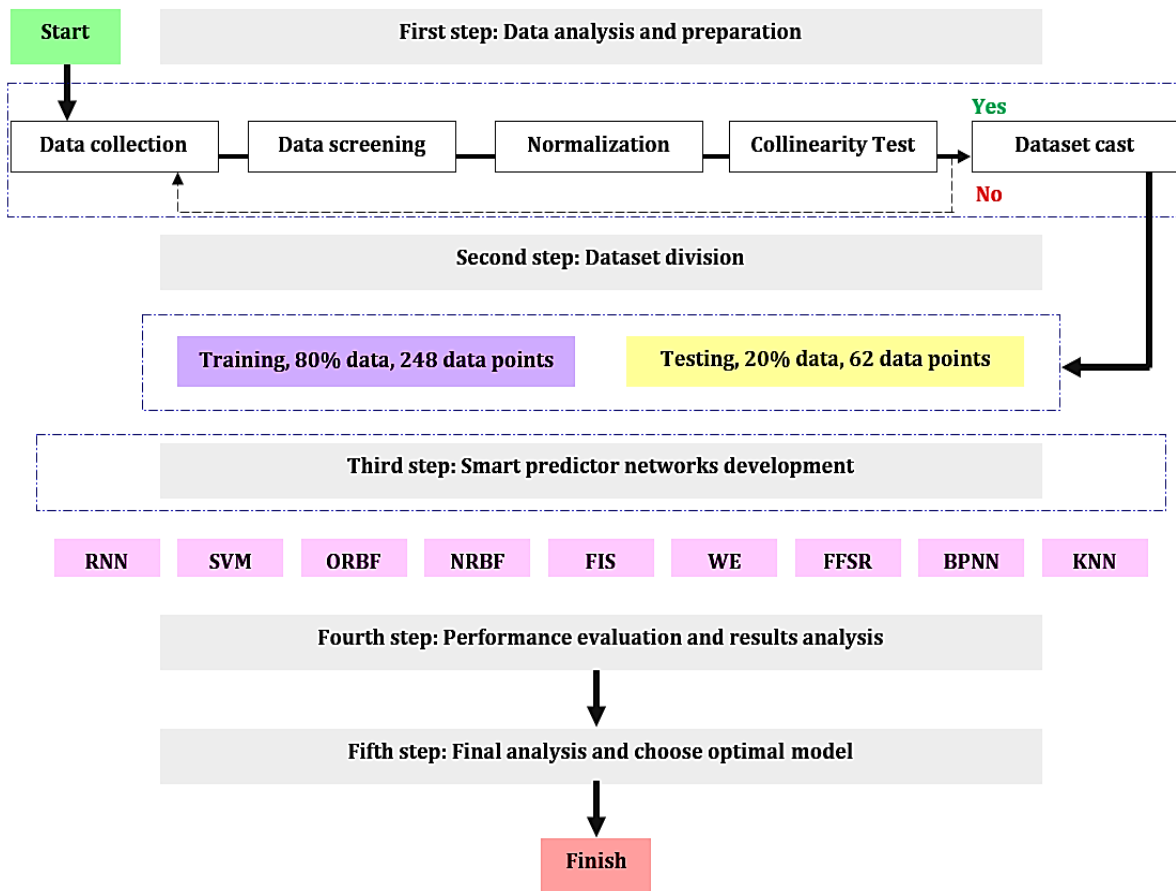


Fig. 1 Schematic diagram of the article steps

The conclusion of the study involved comparing the prediction results of each machine learning model with the measured results using various statistical evaluation indices. The subsequent sections of the article provide background information, a detailed description of the applied machine learning models and their prediction results, a comparison of the prediction results, and a discussion and conclusion. The contributions of this work include;

- the investigation of various underground cavern projects in to obtain more comprehensive data;
- the evaluation of the performance of 9 machine learning methods in predicting sidewall displacement in underground caverns;
- the comparison of the models' behaviors with practical results;
- the sensitivity analysis of parameters based on importance ranking investigation.

2. Machine learning methods

RNN is a type of neural network that is designed to recognize patterns and sequences in data. It has feedback loops that allow information to persist, making it suitable for tasks such as time series analysis and individual data points. SVM is a supervised learning model that is used for

classification and regression tasks. It works by finding the optimal hyperplane that separates different classes in the input data. A fuzzy inference system is a mathematical model that utilizes fuzzy logic to represent and reason with imprecise or vague information. It is often used in control systems and decision-making processes. Fuzzy numbers are employed within the realms of fuzzy logic and fuzzy set theory to tackle scenarios where precise numerical values are unavailable.

Among the various types of fuzzy numbers, the Gaussian fuzzy number stands out as a prominent choice for network training in the present investigation. Gaussian fuzzy numbers offer distinct advantages, enabling the representation of ambiguous information and the management of uncertainty more adeptly compared to conventional numerical methodologies. Their utilization is prevalent in predictive endeavors owing to the bell curve-shaped membership function, facilitating a seamless depiction of potential values surrounding the mean. Gaussian fuzzy numbers prove particularly beneficial in forecasting, risk assessment, and decision-making processes characterized by substantial uncertainty. The mean value signifies the central tendency of a Gaussian fuzzy number, while the standard deviation dictates the dispersion of values around this mean. The probabilistic nature of Gaussian fuzzy numbers renders them well-suited for

Table 1 The statistical metrics of training dataset

Parameters	Y	TS	v	CS	E	φ	C	H	RMR	CH	CW	T	SD	
Unit	kN/m ³	MPa	-	MPa	GPa	degree	MPa	m	-	m	m	days	m	
Type of factor	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input	Output	
N	Valid	248	248	248	248	248	248	248	248	248	248	248	248	
	Missing	62	62	62	62	62	62	62	62	62	62	62	62	
Mean	0.02	0.46	0.28	19.21	30.82	47.75	3.35	492.27	59.05	36.47	53.51	15.01	0.4404	
Std. Error of Mean	0.00	0.01	0.001	1.009	0.806	0.560	0.06	10.66	.6115	.617	0.538	0.562	0.0054	
Median	0.02 ^a	0.50 ^a	0.27 ^a	20.48 ^a	33.89 ^a	45.54 ^a	3.55 ^a	524.7 ^a	58.00 ^a	38.43 ^a	56.02 ^a	15.11 ^a	0.4459 ^a	
Mode	0.02	0.30 ^c	0.32	0.45 ^c	44.52 ^c	51.60 ^c	4.56 ^c	621.0 ^c	65.00	48.00	61.00	9.00	0.22 ^c	
Std. Deviation	0.004	0.27	0.031	15.95	12.75	8.856	1.04	168.69	9.669	9.756	8.511	8.896	0.0864	
Variance	0.00	0.07	0.001	254.6	162.8	78.44	1.09	28458	93.50	95.19	72.45	79.15	0.007	
Skewness	0.54	0.01	0.23	0.033	-0.91	0.380	-0.43	-0.489	0.402	-0.471	-0.829	0.003	-0.277	
Std. Error of Skewness	0.15	0.15	0.15	0.154	0.15	0.154	0.15	0.154	0.154	0.154	0.154	0.154	0.154	
Kurtosis	-0.76	-0.97	-1.45	-1.58	-0.05	-1.16	-0.53	-0.508	0.058	-0.99	-0.38	-1.19	-0.386	
Std. Error of Kurtosis	0.30	0.30	0.30	0.307	0.307	0.307	0.30	0.307	0.307	0.307	0.307	0.307	0.307	
Range	0.01	0.90	0.09	42.05	42.92	27.30	3.62	596.00	36.00	30.00	28.00	30.00	0.40	
Minimum	0.02	0.02	0.25	0.25	2.78	35.80	1.21	142.00	43.00	18.00	35.00	0.00	0.22	
Maximum	0.04	0.92	0.34	42.30	45.70	63.10	4.83	738.00	79.00	48.00	63.00	30.00	0.62	
Sum	6.83	115.2	72.21	4802	7706	11939	839	123069	14764	9118	13379	3753	110.10	
Percentiles	10	0.02 ^b	0.07 ^b	0.25 ^b	0.305 ^b	8.605 ^b	37.52 ^b	1.84 ^b	256.31 ^b	45.20 ^b	21.44 ^b	38.69 ^b	2.687 ^b	0.3220 ^b
	20	0.02	0.18	0.25	0.402	20.92	38.86	2.51	341.60	51.14	26.40	45.37	5.812	0.3648
	50	0.02	0.50	0.27	20.48	33.89	45.54	3.55	524.70	58.00	38.43	56.02	15.11	0.4459
	60	0.02	0.55	0.30	26.53	35.41	49.27	3.79	568.75	60.08	41.13	58.36	18.00	0.4676
	70	0.02	0.59	0.31	32.34	38.02	53.52	3.90	608.34	62.53	43.96	59.89	21.06	0.4919
	75	0.02	0.64	0.31	34.72	40.08	55.26	4.08	625.88	63.90	45.26	60.55	22.68	0.5040
	80	0.03	0.70	0.32	36.27	42.79	57.28	4.37	637.00	65.90	46.20	61.20	24.31	0.5177
90	0.03	0.85	0.33	40.27	45.23	61.32	4.72	700.11	75.00	0.00	62.45	27.26	0.5486	

a: Derived from aggregated data; b: Percentiles computed from aggregated data; c: Multiple modes detected (displaying the smallest value)

prognosticating future outcomes based on historical data and patterns. Their symmetrical bell-shaped configuration allows for a continuous portrayal of uncertainty, while their clearly defined mathematical attributes render them amenable for integration into fuzzy logic systems and decision-making frameworks. In essence, Gaussian fuzzy numbers offer a versatile and efficient structure for modeling fuzzy data and managing uncertainty within predictive contexts. KNN is a non-parametric classification algorithm that uses the similarity of data points to make predictions. It works by finding the k-nearest neighbors to a given data point and using their class.

It should be noted that the key point is not necessarily situated in the middle of the lateral sidewall. However, previous research has demonstrated that the maximum displacement occurs at the key point (Rajabi *et al.* 2017). In this study, ML methods are applied using a dataset of 310 observations from 10 underground cavern projects. Drawing on recent references (Goh *et al.* 2018, Shahmohammadi *et al.* 2020, Sherstinsky 2020, Wang *et al.* 2020, Zhang *et al.* 2020a, b), 12 influential parameters affecting sidewall displacement in underground caverns are taken into account, including tensile strength, unit weight, Poisson ratio, compression strength, rock mass modulus, friction angle, cohesion, overburden, rock mass rating, cavern width and height, and time after excavation.

To incorporate the time elapsed after excavation factor, sidewall displacement is assessed on a daily basis for 30

days following excavation for every project. Afterwards, 80% (248 data points) and 20% (62 data points) of the dataset are allocated for training and testing purposes in the predictive models. Comprehensive statistical summaries of the training and testing datasets are furnished in Tables 1 and 2, correspondingly

Fig. 3 presents the correlation matrix and relationships between input and output parameters, which reveals significant data dispersion. Consequently, the input parameters are normalized within the range of 1 to -1 prior to labels to classify the data. Backpropagation is a common algorithm used for training neural networks. It works by adjusting the weights of the network in the direction that minimizes the error between the actual and predicted outputs. RBF networks are a type of neural network that uses radial basis functions as activation functions. Normalized RBFs have their outputs normalized to sum to one, while ordinary RBFs do not have this constraint. Weight estimation refers to the process of determining the optimal weights for a neural network or other machine learning model. This is typically done through training the model on a labeled dataset and adjusting the weights to minimize the prediction errors. Feed forward stepwise regression is a statistical method used to select the best set of features for a regression model. It works by iteratively adding or removing features based on their contribution to the overall model performance.

Table 2 The statistical metrics of testing dataset

Parameters	γ	TS	ν	CS	E	φ	C	H	RMR	CH	CW	T	SD	
Unit	kN/m ³	MPa	-	MPa	GPa	degree	MPa	m	-	m	m	days	m	
Type of factor	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input	Input	Output	
N	Valid	62	62	62	62	62	62	62	62	62	62	62	62	
	Missing	248	248	248	248	248	248	248	248	248	248	248	248	
Mean	0.02 ^a	0.48 ^a	0.27 ^a	22.07 ^a	31.86 ^a	44.70 ^a	3.16 ^a	451.0 ^a	58.00 ^a	35.60 ^a	53.73 ^a	14.60 ^a	0.446 ^a	
Std. Error of Mean	0.03	0.02 ^c	0.25	7.31 ^c	2.78 ^c	35.8 ^c	1.21 ^c	142.0 ^c	58.00	38.00	45.0	0.00 ^c	0.22 ^c	
Median	0.003	0.26	0.03	14.38	13.05	8.58	1.007	165.2	8.692	10.00	8.80	9.289	0.085	
Mode	0.00	0.06	0.00	206.9	170.4	73.68	1.016	27322	75.55	100.0	77.4	86.28	0.007	
Std. Deviation	0.63	-0.03	0.87	-0.15	-0.77	0.47	-0.36	-0.425	0.060	-0.26	-0.70	-0.01	-0.32	
Variance	0.30	0.30	0.30	0.309	0.30	0.30	0.30	0.309	0.309	0.309	0.30	0.30	0.30	
Skewness	-0.52	-1.02	-0.59	-1.42	-0.50	-1.12	-0.46	-0.469	0.438	-1.13	-0.61	-1.25	0.37	
Std. Error of Skewness	0.60	0.60	0.60	0.608	0.60	0.608	0.60	0.608	0.608	0.608	0.608	0.60	0.60	
Kurtosis	0.01	0.90	0.09	42.05	42.92	27.30	3.62	596.00	36.00	30.00	28.00	30.0	0.41	
Std. Error of Kurtosis	0.02	0.02	0.25	0.25	2.78	35.80	1.21	142.00	43.00	18.00	35.00	0.00	0.22	
Range	0.04	0.92	0.34	42.30	45.70	63.10	4.83	738.00	79.00	48.00	63.00	30.00	0.63	
Minimum	1.60	24.74	16.76	1218	1659.8	2788	184.3	27064	3464	2073	3113	897.0	26.97	
Maximum	0.02 ^a	0.48 ^a	0.27 ^a	22.07 ^a	31.86 ^a	44.70 ^a	3.16 ^a	451.0 ^a	58.00 ^a	35.60 ^a	53.73 ^a	14.60 ^a	0.44 ^a	
Sum	0.03	0.02 ^c	0.25	7.31 ^c	2.78 ^c	35.80 ^c	1.21 ^c	142.0 ^c	58.00	38.00	45.00	0.00 ^c	0.22 ^c	
Percentiles	10	0.02 ^b	0.04 ^b	0.0 ^{b,d}	0.334 ^b	5.484 ^b	36.60 ^b	1.50 ^b	195.0 ^b	44.23 ^b	19.60 ^b	37.00 ^b	2.250 ^b	0.34 ^b
	20	0.02	0.12	0.25	1.073	13.83	38.80	2.33	341.0	50.00	24.33	43.00	5.25	0.38
	50	0.02	0.48	0.27	22.07	31.86	44.70	3.16	451.0	58.00	35.60	53.73	14.60	0.44
	60	0.02	0.54	0.27	26.81	33.82	45.81	3.52	518.3	59.71	38.84	56.30	18.50	0.46
	70	0.02	0.56	0.28	31.46	35.24	52.55	3.75	563.5	61.60	41.36	58.50	21.60	0.49
	75	0.02	0.59	0.30	33.51	36.02	54.46	3.82	572.5	62.80	42.90	59.35	23.00	0.50
	80	0.02	0.61	0.31	35.17	37.59	56.11	3.87	597.5	64.00	44.70	60.05	24.25	0.52
90	0.03	0.73	0.32	37.98	42.83	59.32	4.32	642.0	71.12	47.53	61.61	27.80	0.55	

a: Derived from aggregated data; b: Percentiles computed from aggregated data; c: Multiple modes detected (displaying the smallest value)

3. Modeling procedure

3.1 Database preparation

The diagram in Fig. 2 illustrates the geometric layout of an underground cavern and the specific points used in the analysis. Essentially, this figure provides a schematic representation of an underground cavern to highlight the key point on the lateral sidewall.

It should be noted that the key point is not necessarily situated in the middle of the lateral sidewall. However, previous research has demonstrated that the maximum displacement occurs at the key point (Rajabi *et al.* 2017). In this study, ML methods are applied using a dataset of 310 observations from 10 underground cavern projects. Drawing on recent references (Goh *et al.* 2018, Shahmohammadi *et al.* 2020, Sherstinsky 2020, Wang *et al.* 2020), 12 influential parameters affecting sidewall displacement in underground caverns are taken into account, including tensile strength, unit weight, Poisson ratio, compression strength, rock mass modulus, friction angle, cohesion, overburden, rock mass rating, cavern width and height, and time after excavation.

To account for the time after excavation parameter, sidewall displacement is measured once daily for 30 days' post-excavation for each project. Subsequently, 80% (248 data points) and 20% (62 data points) of the dataset are used for training and testing in the prediction models. A summary

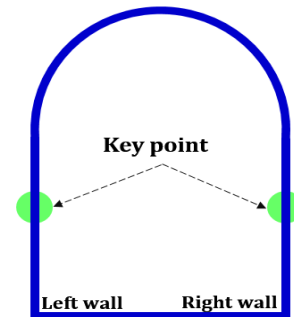


Fig. 2 Geometrical layout of an underground cavern

statistical analysis of the training and testing datasets is provided in Tables 1 and 2, respectively.

Fig. 3 presents the correlation matrix and relationships between input and output parameters, which reveals significant data dispersion. Consequently, the input parameters are normalized within the range of 1 to -1 prior to modeling by the ML methods to mitigate the potential overfitting effect during the adjustment process.

Furthermore, visual descriptive statistics, such as boxplots in Fig. 4, are conducted on the datasets. These plots depict the distribution of the parameters in three modes – training, testing, and all data points. It is evident that the datasets are non-symmetrical as the median line is not centrally located in the box for all parameters, indicating the presence of outliers. The identification and



Fig. 3 The correlation matrix and relationships between input and output parameters affecting sidewall displacement

Table 3 Summary of factors and hyper-parameters of the ML applied algorithms

Model	Factors and hyper-parameters			
RNN	Optimizer = Adam Validation split = 0.15	Loss = Huber	Batch-size = 32	NP,shape (310,13)
BPNN	Learning rate = 0.1	np. random. seed (10)		Iterations = 1000
KNN	Normalized scale features: K= 5 Mean of nearest neighbor values computation = Euclidean metric	Distance computation = Euclidean Metrix Set seed for mersenne Twister = 0	Prediction for scale target = Focal = Yes	Distance
RBF	Hidden layer activation function = Softmax time = 0:00:00.34 Error function = sum of squares	Output layer activation function = Identify Rescaling method for scale dependents = Standardized	Training	
SVM	gam = 1.2297 function = lin-kernel optimization terminated successfully (TolFun criterion)	F(x) = 0.0062409	cost function = crossvalidateLSSVM	kernel
WE	Power range = -2	through = 2	yp = 310*1 double	by = 0.5
FFSR	Confidence level = 0.95 forward stepwise default combining rule for continuous target = mean	criteria for entry = information criterion (AICC)	Model selection method =	
FIS	one method = prod method = wtaver Input = 1*12 struct = 1*1 struct	or method = prober	imp method = prod	Agg method = max Defuzzy output

removal of outliers and clusters are essential in data processing to improve the reliability of forecasting models. Additionally, the absence of extreme values for any of the parameters is evident in Fig. 4.

The dataset underwent principal component analysis (PCA), a multivariate statistical method widely employed to probe disparities, discern trends, and streamline the complexity of issues, such as the abundance of independent variables. In PCA, linear combinations of original variables, termed principal components (PCs), are employed to most effectively elucidate distinctions across datasets. The coefficients (eigenvalues) and percentage of variance explained by the PCs are depicted in Fig. 5, as these scree charts aid in identifying which PCs offer the most insightful portrayal of dataset variability. Furthermore, the component plot in rotated space, showcased in Fig. 6, unveils that the dataset lacks clear natural groupings and stands as an outlier in this regard.

3.2 Implementation of the ML models

To deploy the machine learning (ML) models, we utilized the computational prowess of the Google Colab environment, seamlessly integrated with the Python 3 programming language. Google Colab stands out as a prominent free platform tailored for scientific computing in Python, offering not only a cost-efficient solution but also streamlining package management and execution processes. Our computational tasks were executed on a robust Intel® Core™ i5-1155G7 CPU operating at 2.5 GHz, coupled with a 16 GB RAM capacity, ensuring swift and precise performance. The ML models underwent optimization using training datasets to achieve optimal sidewall displacement estimation. This optimization process entailed fine-tuning the models' hyperparameters to attain superior performance. In this study, we adopted the trial-and-error approach to meticulously adjust the hyperparameters, involving

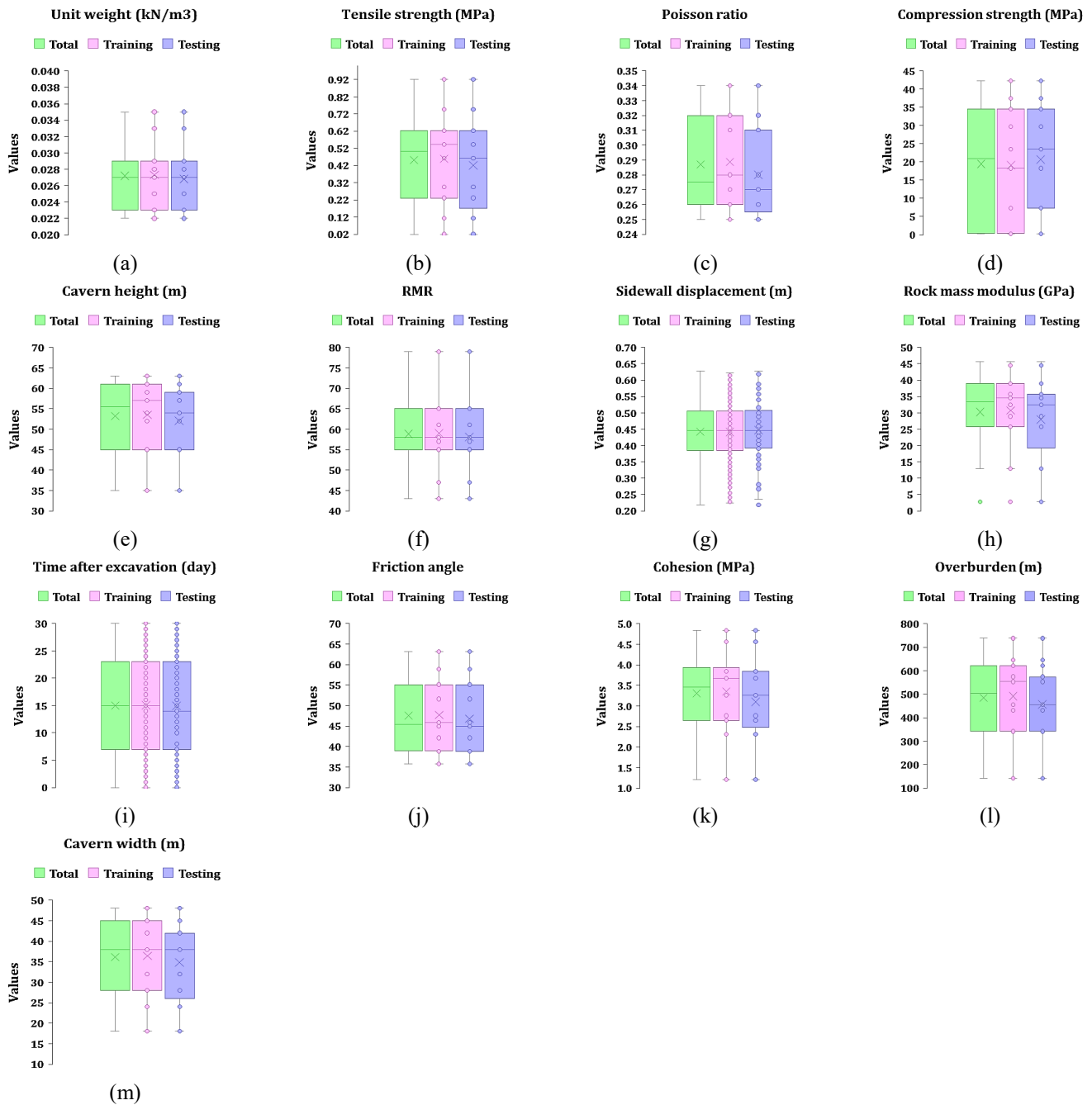


Fig. 4 The box plot diagrams of input and output factors defined in the database for three category types

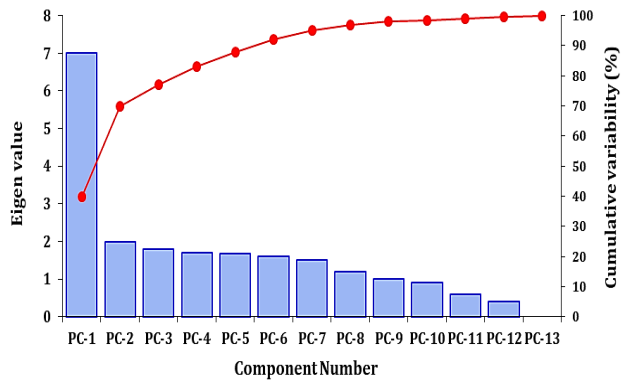


Fig. 5 Scree plot for the first 13 PCs

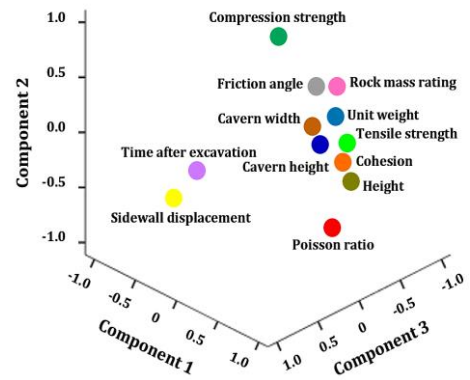


Fig. 6 The component plot in rotated space

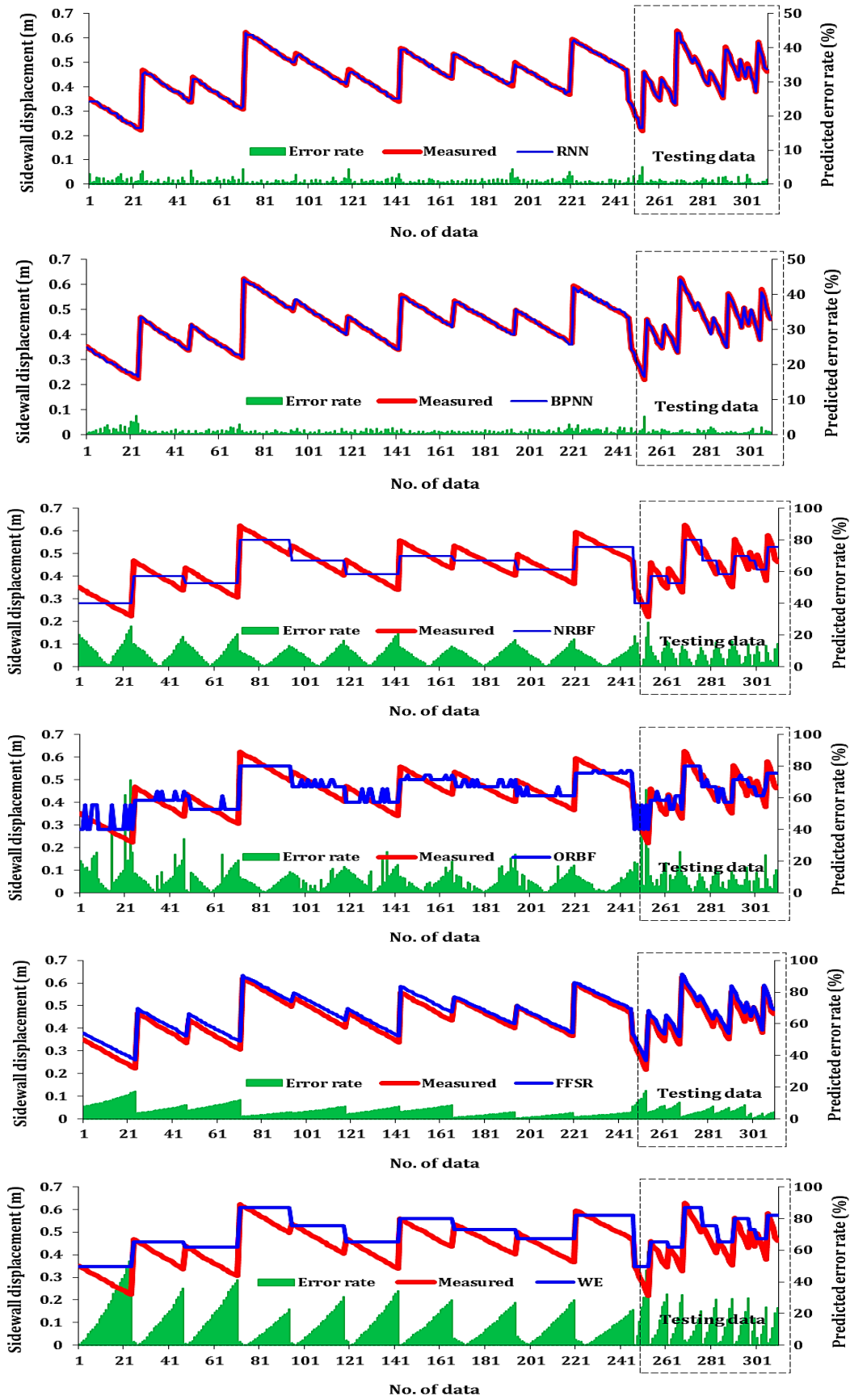


Fig. 7 Comparison of the ML results with actual values of sidewall displacement

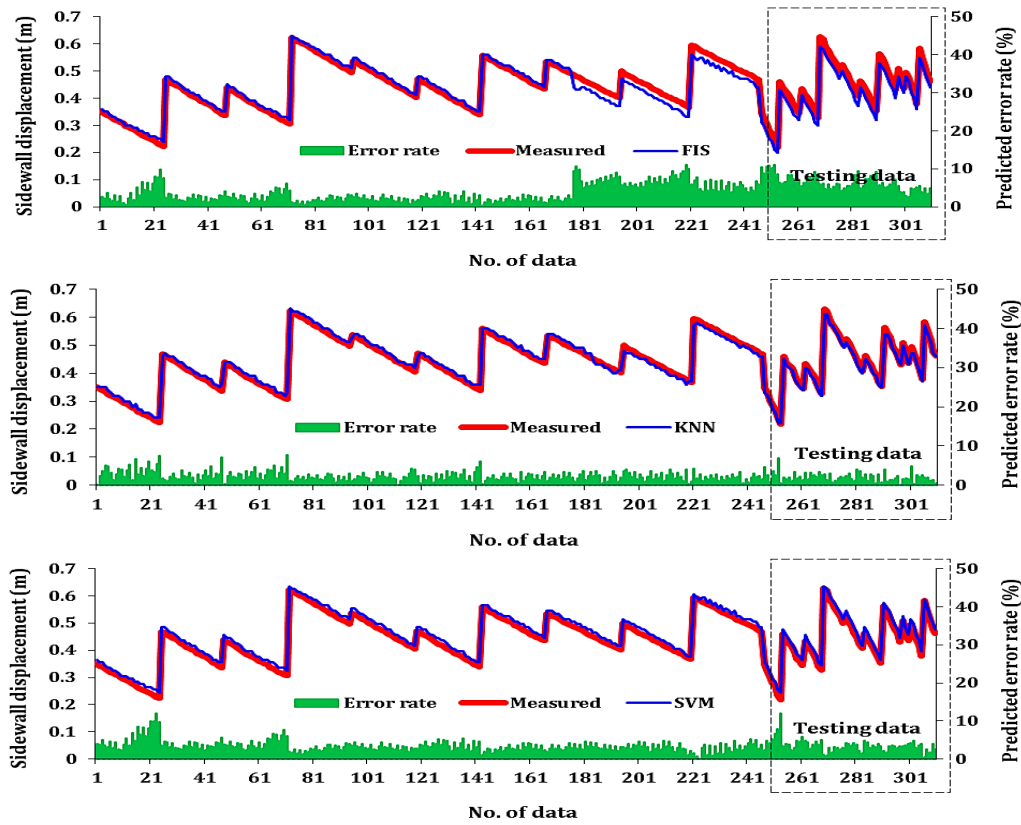


Fig. 7 Continued-

exhaustive iterations to resolve intricate challenges before reaching the most effective solution. The refined hyperparameters and parameters for each ML method are outlined in Table 3.

3.3 Evaluation metrics

Utilization of loss functions and evaluation metrics is essential in understanding complex systems. Regardless of the field, it is crucial to evaluate these forecasting outcomes and results of analysis. Forecasts are rigorously compared to relevant observations through various statistical measures, known as indices, to understand differences between forecasted and actual values. These differences provide insight into the model's performance and its consistency with real-world observations. This study compares the prediction results of ML models for sidewall displacement with measured results using statistical evaluation metrics including coefficient of determination (R^2), mean absolute deviation (MAD), mean squared error (MSE), log-cash loss (LCL), and root relative squared error (RRSE) (Eqs. (1)-(5)).

$$R^2 = 1 - \frac{\text{sum squared regression}}{\text{sum of squares total}} \quad (1)$$

$$MSE = \frac{1}{n} \sum (A - P)^2 \quad (2)$$

$$MAD = \frac{\sum |P - \text{average}(P)|}{n} \quad (3)$$

$$\text{Logcash}(t) = \sum_{i=1}^n \log(\cosh(P - A)) \quad (4)$$

$$RRSE = \sqrt{\frac{\sum_{i=1}^n (A - P)^2}{\sum_{i=1}^n (A - \text{average}(A))^2}} \quad (5)$$

where P and A indicate the predicted and actual values, respectively; and n is the number of data.

4. Results and analysis

This section presents a concise overview of several frequently utilized algorithms for sidewall displacement prediction, including recurrent neural network (RNN), back-propagation neural network (BPNN), K-nearest neighbors (KNN), normalized and ordinary radial basis function (NRBF, ORBF), support vector machine (SVM), weight estimation (WE), feed-forward stepwise regression (FFSR), and fuzzy inference system (FIS).

These algorithms have gained popularity in many fields of engineering and have been used for prediction of target factors in tunnelling with several aspects over the years as well. The description and background of these methods can be found in the literature and will not be repeated here. Upon the completion of fine-tuning the ML models with the training datasets, an evaluation of their effectiveness can be conducted. This assessment will utilize quantitative metrics to compare the efficacy of different ML models.

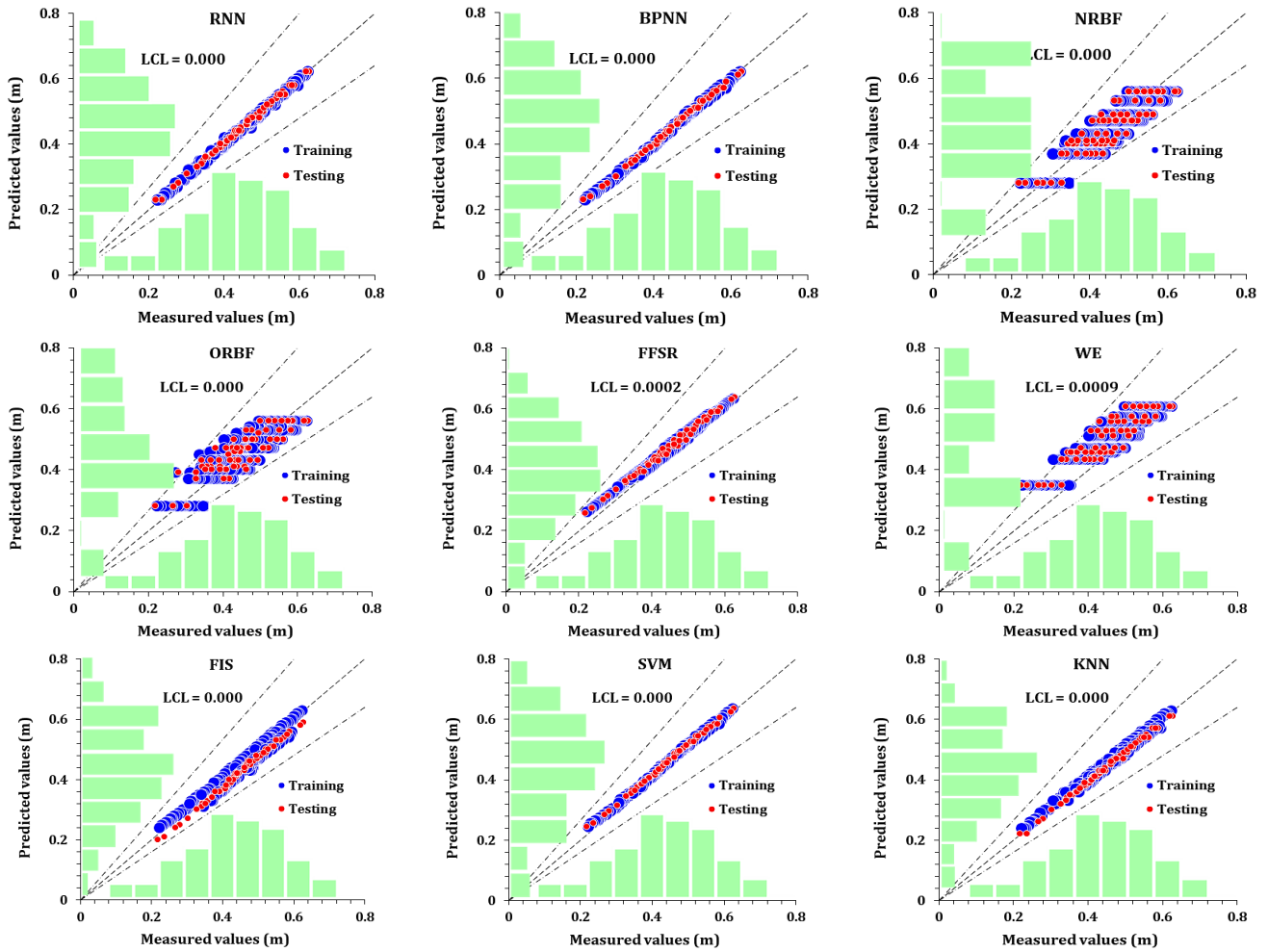


Fig. 8 The correlation between measured and predicted values as well as Pareto histograms of relative errors

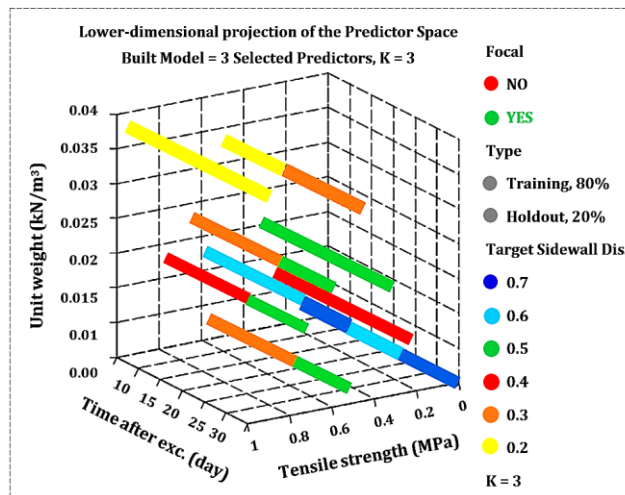


Fig. 9 The lower-dimensional projection of the predictor space with $K = 3$ based on KNN for sidewall displacement prediction

The comparison between the ML models' estimated results and those obtained from the actual condition is illustrated in Fig. 7. For more clarification and observation, the correlation between the predicted values obtained from machine learning predictor networks and measures values

of sidewall displacement as well as Pareto histograms of relative error is presented in Fig. 8 considering the LCL evaluation metric.

Notably, all models demonstrate high accuracy in estimating the sidewall displacement, with the RNN and

Table 4 Performance investigation of the applied ML models for the sidewall displacement prediction using evaluation metrics

Total dataset									
	RNN	BPNN	NRBF	ORBF	FFSR	WE	FIS	SVM	KNN
RMSE	0.0006	0.0000	0.0040	0.0040	0.0016	0.0001	0.0005	0.0008	0.0000
MAD	0.0003	0.0004	0.0005	0.0006	0.0003	0.0005	0.0003	0.0004	0.0003
RSE	0.0019	0.0019	0.0789	0.3461	0.0584	0.0663	0.0012	0.0056	0.0012
RRSE	0.0439	0.0439	0.2809	0.5883	0.2416	0.2574	0.0351	0.0747	0.0351
R ²	0.9969	0.9975	0.7902	0.7255	0.9917	0.7834	0.9445	0.9975	0.9837
LCL	0.0000	0.0000	0.0000	0.0000	0.0002	0.0008	0.0000	0.0000	0.0000
Training sub-dataset									
	RNN	BPNN	NRBF	ORBF	FFSR	WE	FIS	SVM	KNN
RMSE	0.0007	0.0000	0.0045	0.0045	0.0017	0.0002	0.0006	0.0009	0.0000
MAD	0.0004	0.0005	0.0006	0.0007	0.0004	0.0006	0.0004	0.0005	0.0004
RSE	0.0019	0.0019	0.0790	0.3462	0.0584	0.0663	0.0012	0.0056	0.0012
RRSE	0.0439	0.0439	0.2810	0.5884	0.2416	0.2574	0.0352	0.0747	0.0351
LCL	0.0000	0.0000	0.0000	0.0000	0.0002	0.0008	0.0000	0.0000	0.0000
Testing sub-dataset									
	RNN	BPNN	NRBF	ORBF	FFSR	WE	FIS	SVM	KNN
RMSE	0.0002	0.0002	0.0061	0.0077	0.0037	0.0024	0.0036	0.0020	0.0011
MAD	0.0027	0.0027	0.0025	0.0027	0.0026	0.0023	0.0027	0.0027	0.0027
RSE	0.0019	0.0019	12.536	8.6626	1.2691	0.0353	3.0569	0.8836	0.3064
RRSE	0.0439	0.0439	3.5407	2.9432	1.1265	0.1878	1.7484	0.9400	0.5535
LCL	0.0000	0.0000	0.0003	0.0005	0.0001	0.0020	0.0001	0.0000	0.0000

BPNN models achieving the highest accuracy (LCL = 0.00000) and the WE model achieving the highest accuracy (LCL = 0.0008). Additional statistical measures such as R², MSE, RRSE, and MAD are employed to further evaluate the efficacy of the ML models alongside the LCL metric. The concept of lower-dimensional projections within the framework of the K-nearest neighbors (KNN) model pertains to the reduction of feature space dimensions with the aim of optimizing the efficiency and efficacy of the KNN algorithm. This technique involves converting the original high-dimensional dataset into a lower-dimensional format while retaining crucial information necessary for accurate predictions. By diminishing the number of dimensions, the computational intricacy of the KNN model can be lessened, resulting in quicker processing times and potentially enhanced performance. Lower-dimensional projections play a vital role in data visualization, pattern recognition, and the refinement of the KNN model to achieve superior predictive accuracy. The lower-dimensional projections of the predictor space concerning input variables within the KNN network are illustrated in Fig. 9.

The statistical metrics for each model considering three categories including total dataset, training and testing sub-dataset are presented in Table 4, highlighting the comprehensive approach to assessing the models' performance. The ranking of each model is then depicted in numerical form in Table 5, with a visual representation of this information provided in Fig. 10. These results indicate that the BPNN and KNN models (score = 48) outperforms the other models in terms of accuracy. However, the normalized and ordinary RBF models indicate the lower accuracy with 27 and 22 scores; respectively. The ranking order based on the prediction accuracy of each model is as

follows: BPNN, KNN → FIS → RNN → SVM → FFSR → WE → NRBF → ORBF.

5. Sensitivity analysis

To put the study's findings into perspective, a sensitivity analysis was conducted to pinpoint the most influential model parameters. This comprehension is vital for simplifying data intricacies and guarding against model overfitting. Employing the predictor normalized importance (PNI) technique for sensitivity analysis, the study delved into feature selection. PNI harnesses the principles of information gain from information theory, translating them into practical applications through machine learning methods. Notably adept at handling categorical input and output data, PNI can be tailored to accommodate numerical data as well. The efficacy of PNI is gauged by the extent of entropy it eradicates. A substantial PNI value indicates the feature's significance in model training, warranting greater consideration in the final evaluation. Conversely, a low PNI score denotes minimal or negligible correlation between the attribute and the desired outcome.

The study presents the estimated PNI scores for various inputs utilizing three prominent machine learning models: BPNN, KNN, and FIS. These models were selected for their high accuracy in predicting sidewall displacement, a critical factor in assessing the stability of caverns.

The results of the BPNN model, illustrated in Fig. 11, demonstrate that elastic modulus and cohesion factors exert the most significant influence on sidewall displacement. These geotechnical features play a crucial role in the structural integrity of caverns. Conversely, Poisson ratio and time after excavation are found to have the least impact on sidewall displacement.

Table 5 Ranking score of the results of applied ML models based on several evaluation metrics

	RMSE	RANK	MAD	RANK	RSE	RANK	RRSE	RANK	R ²	RANK	LCL	RANK
RNN	0.000611	6	0.00033	6	0.001925	8	0.043874	8	0.9969	8	5.98E-06	8
BPNN	4.27E-05	9	0.000363	5	0.001925	8	0.043874	8	0.9975	9	4.9E-06	9
NRBF	0.004018	3	0.000518	3	0.078924	4	0.280935	4	0.7902	4	4.9E-06	9
ORBF	0.004018	3	0.000553	2	0.346084	3	0.588289	3	0.7255	2	4.9E-06	9
FFSR	0.001555	4	0.000329	7	0.058368	6	0.241595	6	0.9917	7	0.000242	5
WE	0.000149	8	0.00047	4	0.066254	5	0.257399	5	0.7834	3	0.000872	4
FIS	0.000525	7	0.000308	8	0.001235	9	0.035147	9	0.9445	5	5.98E-06	8
SVM	0.000809	6	0.000363	5	0.005574	7	0.074657	7	0.9975	9	2.28E-05	7
KNN	4.27E-05	9	0.000304	9	0.001235	9	0.035147	9	0.9837	6	5.05E-05	6

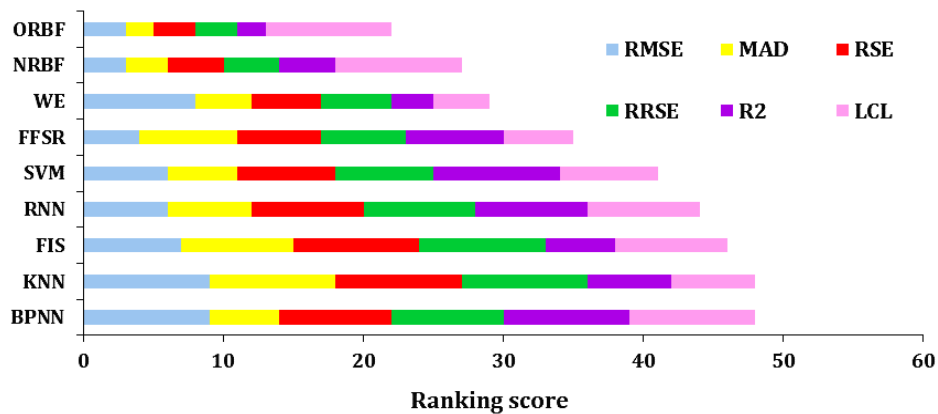


Fig. 10 Ranking score of the applied ML models for the sidewall displacement prediction



Fig. 11 The score of sensitivity analysis for input parameters based on PNI technique using BPNN algorithm

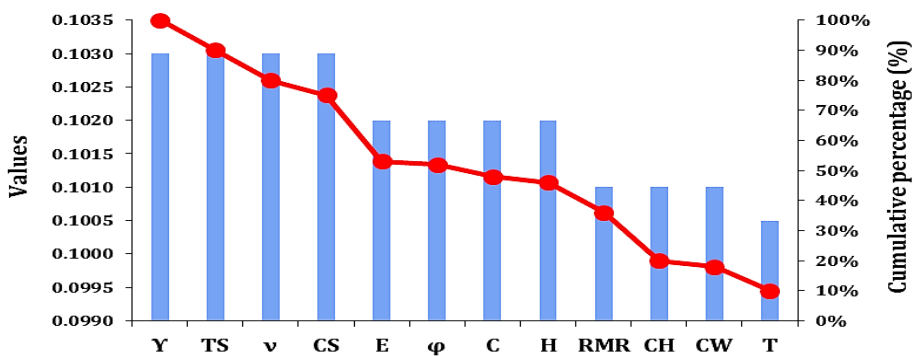


Fig. 12 The score of sensitivity analysis for input parameters based on PNI technique using KNN algorithm

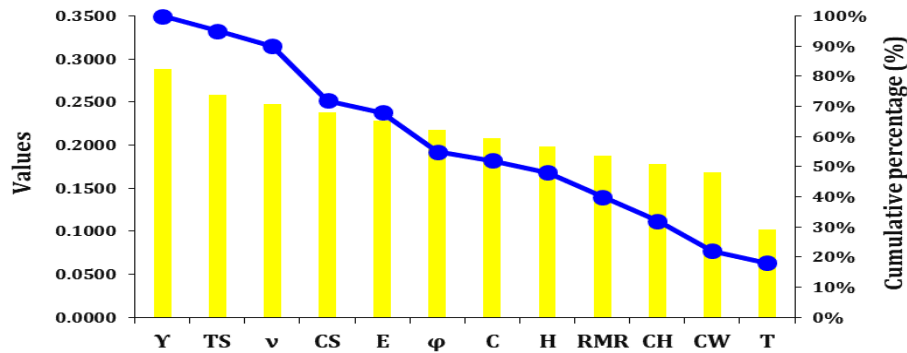


Fig. 13 The score of sensitivity analysis for input parameters based on PNI technique using FIS algorithm

Similarly, the PNI scores derived from the KNN model, as depicted in Fig. 12, reveal that unit weight and tensile strength are the most influential factors affecting sidewall displacement. In contrast, cavern width and time after excavation contribute minimally to the displacement of cavern walls.

Moreover, the FIS model also highlights unit weight and tensile strength as the most influential factors on sidewall displacement, while cavern width and time after excavation exhibit the least impact (Fig. 13). These findings emphasize the significance of geotechnical properties of material and cavern dimensions in determining the stability of caverns with respect to displacement.

Upon integrating the results from the three models, it is evident that cohesion, unit weight, and cavern width stand out as the key determinants of sidewall displacement. The geotechnical properties of materials, particularly cohesion and tensile strength, play a critical role in supporting the structural stability of caverns. Likewise, the physical properties of the materials, as reflected in unit weight, significantly influence sidewall displacement. Additionally, the dimensions of the cavern, represented by cavern width, play a pivotal role in assessing the displacement and overall stability of the structure.

The implications of these findings extend to engineering and construction practices related to cavern stability. By recognizing the paramount influence of geotechnical properties of materials, and cavern dimensions, engineers and geotechnical experts can make informed decisions regarding the design and maintenance of caverns. Understanding the specific factors that contribute to sidewall displacement enables stakeholders to implement targeted measures for enhancing the stability and safety of cavern structures.

6. Conclusions

Efforts will be directed towards enhancing the ML methods for predicting sidewall displacement of underground caverns, with the aim of developing more efficient and accurate algorithms. This study utilized nine machine learning (ML) methods, including recurrent neural network, back-propagation neural network, K-nearest neighbors, normalized and ordinary radial basis function,

support vector machine, weight estimation, feed-forward stepwise regression, and fuzzy inference system to examine their efficacy in forecasting the sidewall displacement of underground caverns. A dataset comprising 310 observations was employed in training the models, with consideration given to 12 influential parameters affecting the sidewall displacement of the underground caverns. The dataset was partitioned into 80% (248 data points) for training the prediction models and 20% (62 data points) for validation. The predictive performances of the models were then evaluated by comparing their results with measurements using various statistical evaluation indices and loss functions.

The BPNN model outperformed the other ML methods, yielding the most accurate predictions for the sidewall displacement of underground caverns, as evidenced by its high $R^2 = 0.9969$, low RMSE = $4.27E-05$ and LCL = $4.9E-06$. Conversely, the ORBF model demonstrated the least accuracy, with an R^2 value of 0.7255, RMSE of 0.004018, and LCL = $4.9E-06$.

The study's results include the estimated PNI scores for all inputs based on the top-performing models, including BPNN, KNN, and FIS. For instance, the PNI scores for the BPNN algorithm indicate that factors such as elastic modulus and cohesion have the greatest influence on sidewall displacement, whereas Poisson ratio and time after excavation have the least impact. Similarly, the PNI scores for the KNN and FIS algorithms reveal the most influential factors on sidewall displacement including unit weight and tensile strength, as well as those with the least impact such as cavern width and time after excavation. Overall, this study underscores the potential of ML methods in predicting sidewall displacement of underground caverns and highlights opportunities for advancing these techniques in geotechnical engineering applications.

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Conflict of interest

We declare that there is no conflict of interest.

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