Shahrood University of Technology

Journal of Mining and Environment (JME)

Journal homepage: www.jme.shahroodut.ac.ir

Iranian Society of Mining Engineering (IRSME)

Artificial Intelligence Tool for Prediction of Mine Tailings Dam Slope Stability

Kapoor Chand, Ved Kumar, Priyanshu Raj, Nikita Sharma, Amit Kumar Mankar, and Radhakanta Koner*

Department of Mining Engineering, Indian Institute of Technology (Indian School of Mines), Dhanbad 826004, Jharkhand, India

Article Info

Received 29 May 2024

Received in Revised form 18 July 2024

Accepted 4 August 2024

Published online 4 August 2024

DOI: 10.22044/jme.2024.14602.2754

Keywords

Tailings dam stability

Numerical Modelling

Factor of safety

Machine Learning

Abstract

Failure of tailings dams is a major issue in the mining industry as it critically impacts the environment and life. A major cause of the failure of tailings dams is the unplanned depositing of tailings and the increase in saturation due to rainfall events. This study using numerical modelling and artificial intelligence techniques (like MLR, SVR, DT, RF, and XGB) aims to predict the slope stability of tailings dams to avoid failure. The stability of tailings dams is analysed using the finite difference method (FDM), which computes the factor of safety (FoS) using the shear strength reduction (SSR) technique. This investigation mainly focuses on the geotechnical and geometric parameters of the tailings dam, such as density, cohesion, friction angle, saturation, embankment height, slope angle and haul road width. Results of numerical modelling have been used for developing ML models and predicting slope stability. The efficiency of ML models was analysed based on the R2 and root mean square error (RMSE), mean squared errors (MSE), and mean absolute error (MAE). The XGB algorithm proved to be the most effective as it gave the highest accuracy and lowest RMSE value compared to other ML models. AI tool was developed based on the ML model results for dam slope stability prediction. The developed AI tool will help understand the role of saturation and geometry parameters in embankment stability at the initial level of investigation.

1. Introduction

The tailings dam embankment structure is susceptible to unplanned deposition and design. It is designed to effectively contain and manage mine waste, commonly referred to as tailing material (iron ore waste, fly ash). The iron ore waste is deposited in the mine area in a tailings dam. There are three types of waste based on the construction approach: downstream, centerline, and upstream, that result in cost savings and efficient waste management [1]. In recent decades, the metal mining industry has faced many issues related to tailings dam failures. Every year up to five tailings dams fail worldwide [2], and the failure of tailings dams creates severe environmental problems and fatalities [3]. Tailings dam failure has seen on a global scale from 1915 to 2020 as shown in Figure 1. Therefore, tailings dam stability analysis is essential for avoiding failure-related issues.

✉ *Corresponding author: rkoner@iitism.ac.in (R. Koner)*

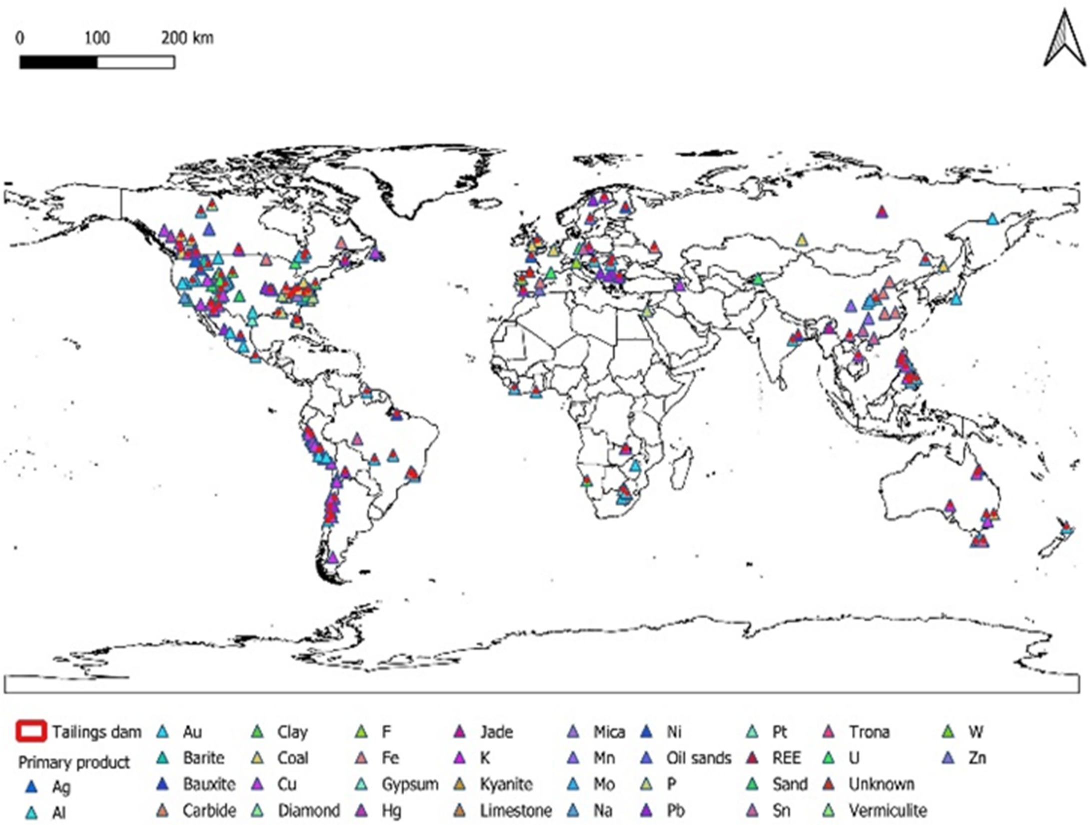

Figure 1. Statistical distribution of tailings dam failures on a global scale [4]

In the past, numerous in-depth investigations have been carried out on the environmental impact, failure mechanism, and slope stability of tailings dams. The finite element method (FEM) [5] and limit equilibrium method (LEM) [6] have been employed for slope strength analysis, such as dam slope stability, displacement analysis [7] and parametric study [8]. However, it was found that each approach has its benefits and drawbacks. Therefore, there is a need for a robust and reliable approach for accurate stability analysis under field conditions. In several studies, the main reason for the tailings dam failure was found to be liquefaction [9]. Liquefaction can significantly affect the slope stability of tailings dams, leading to potentially catastrophic consequences. Examples of failure are Merriespruit in South Africa [10], Fundao in Brazil [11], Cadia Valley in Australia [12] and Brumadinho in Brazil [13]. Earthquakes and high-intensity precipitation typically cause changes in the stress, pore water pressure and seepage, which cause a slope to become unstable. Numerous factors have contributed significantly to the failure of the tailings dam, including foundation failure, excessive precipitation, seismic liquefaction, seepage, inadequate freeboard, and an increase in the phreatic surface [14]. The primary variables contributing to the failure were meteorological conditions, especially irregular rainfall and snowfall. It has been found that 66% of the collapsed tailings dams were constructed utilising the upstream (U/S) type of embankment construction [14].

In recent years, machine learning (ML) algorithms have been widely used for field applications such as rock and soil slope stability analysis for geotechnical investigations. In Chile, artificial intelligence (AI) algorithms were used in tailings dam stability analysis [15]. The dam stability prediction involves different ML algorithms, namely multiple linear regression (MLR) [10], decision tree (DT) [11], random forest (RF) [12], support vector regression (SVR) [13] and extreme gradient boosting (XGB) [16], which were chosen for excellent performance in geotechnical investigation and the dam slope stability prediction [17].

This study aimed to develop an AI tool for predicting tailings dam slope stability. In the initial phase, 767 numerical models were solved to obtain the slope FoS with different slope stability affecting parameters such as height, slope angle, haul road width, material properties, and saturation conditions. In addition, this investigation developed ML models for slope stability prediction and analysed the efficiency of ML models based on R^2, RMSE, MAE and MSE. Finally, a user interface (UI) was developed on a web page for the dam slope stability prediction, which will help make a decision for the tailings dam slope stability. The results of this investigation show the significance of ML in the prediction and management of tailings dam stability.

2. Background of Study – Mine Tailings Dam

Figure 2 depicts the basic structure of a tailings dam, with H representing the height of the dam, θ denoting the slope angle of the embankment, and w indicating the width of the haul road. The foundation of the tailings dam is 15 m, and the freeboard height is 5 m.

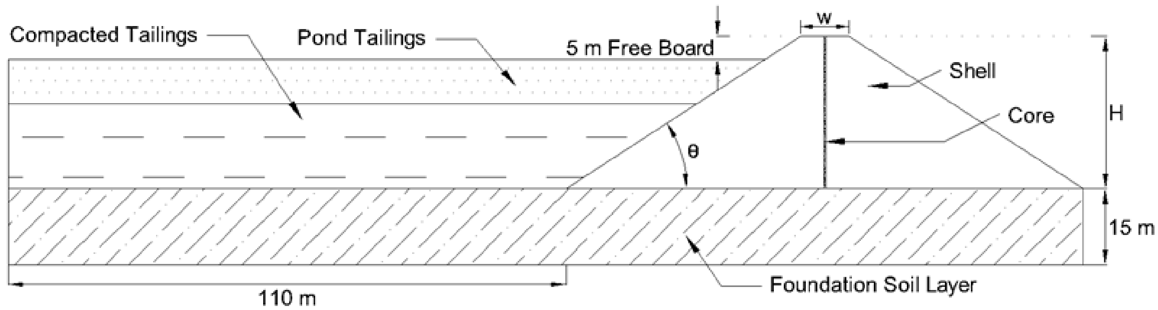

Figure 2. Schematic diagram of the tailings dam

The width of the shell is dependent on the embankment height (H), slope angle (θ) and haul road width (w). The ratio between the height of compacted tailings and pond tailings is in the range of 7:3 to 8:2. The geotechnical parameters of the tailings dam are listed in Table 1, such as unit weight (kN/m^3), cohesion (Pa), angle of internal friction (ϕ), shear modulus (MPa), Poisson ratio, porosity, and permeability (k) (m/sec). The scheme of the tailings dam embankment slope stability analysis using the numerical simulation and ML approaches is shown in Figure 3.

Table 1. Geotechnical parameters of tailings dam [17]

	Tailings dam embankment				
Geotechnical parameters	**Shell**	**Core**	**Pond tailings**	**Compacted tailings**	**Foundation soil**
Unit weight (kN/m^3)	18.30	16.40	19.00	19.00	18.30
Cohesion (Pa)	31.25	35.00	14.70	14.70	31.25
Angle of internal friction (ϕ)	28.00	28.00	12.00	15.20	28.00
Shear modulus (MPa)	190.25	53.56	45.64	95.39	217.35
Poisons ratio (υ)	0.30	0.40	0.35	0.35	0.20
Porosity (%)	0.30	0.25	0.25	0.25	0.30
Permeability (m/sec)	1e-8	1e-10	1e-8	1e-8	1e-8

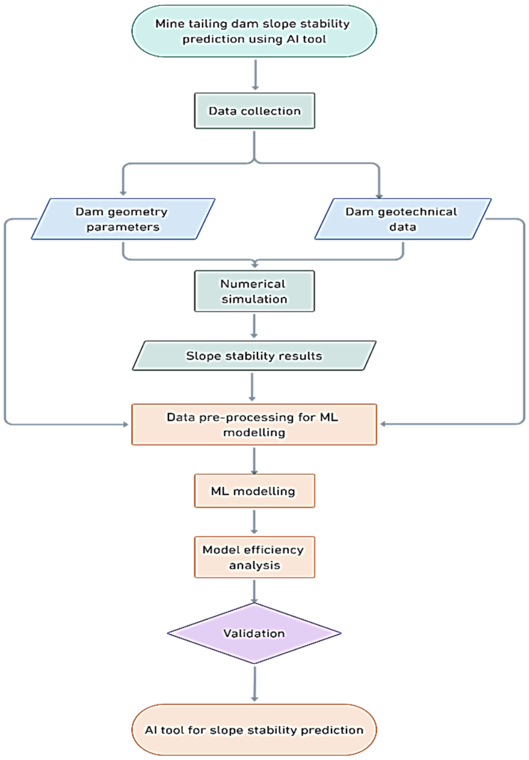

Figure 3. The flowchart illustrates the approach for the tailings dam stability prediction

3. Numerical Modelling

Numerical simulation has been widely used for slope stability analysis, such as rock slope stability [18], [19], mine waste dump design and stability [20], [21], [22] and tailings dam stability [14]. FEM and FDM are employed for the slope stability and deformation analysis. Dam slope FoS is used for the slope stability prediction in this investigation. FoS is essential for slope design and stability analysis. Rock, dump and tailings dam slope stability are analysed using FoS. If the slope stability is 1.2, then the slope will be stable and below 1 it indicates the unstable slope [23]. Therefore, this study uses the FoS for the dam slope stability prediction using ML models. Flac^{2D} computing application was employed for the dam slope FoS calculation. Mohr-Coulomb constitutive failure criterion was used for the dam slope FoS calculation based on the SSR method. The SSR approach is employed in FoS calculations to gradually decrease the shear strength (cohesion and friction angle), typically by applying the Mohr-Coulomb failure criterion [22]. The SSR equations for properties like cohesion and internal angle of friction are:

$$C_{trial} = \left(\frac{1}{F^{trial}}\right) * c \quad (1)$$

$$\varphi_{trial} = \tan^{-1}\left(\left(\frac{1}{F^{trial}}\right)\tan(\varphi)\right) \quad (2)$$

Where, the F^{trial} is FoS trial for stability calculation, C_{trial} and φ_{trial} are gradually reduced values of shear strength parameters (cohesion and angle of friction). c will be the actual cohesion value, and φ the actual internal angle of friction.

4. Machine Learning

Many researchers have used AI algorithms such as ML for slope stability prediction [24] and rock mass classification [25]. ML to slope stability prediction has positive outcomes. MLR, DT, RF, SVR, and XGB were used for tailings dam slope stability prediction.

4.1. Multiple Linear Regression

MLR is a commonly employed statistical method in machine learning that establishes a linear association between a dependent variable and multiple independent variables [26], [27]. Using a dataset with known values for both dependent and independent variables, the model is trained to estimate the coefficients that best fit the data, which can be used for the predictions of new data by putting the values of the independent variables. The fundamental concept of the MLR model is to get the best-fitting linear equation for given data sets (Figure 4). Most linear regressions are fitted using the least squares method [28]. The research conducted by Erzin and Cetin [29] demonstrates the utilisation of the multiple regression model. MLR has been utilised to predict slope failures and landslides [30], [31].

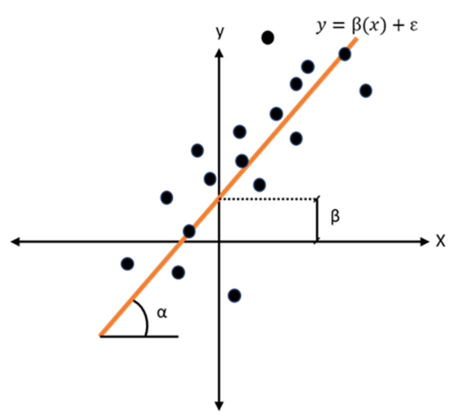

Figure 4. A schematic diagram of simple linear fitting [32]

The multiple linear regression can be mathematically represented as:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \quad (3)$$

Where Y variable is dependent or predicted, the y-intercept determines the slope of Y, that is, when $x_1, x_2 \ldots, x_k$ are zero, Y will be β_0. The regression coefficients $\beta_1, \beta_2, \ldots, \beta_k$ represent the change in Y because of one-unit change in $x_1, x_2 \ldots, x_k$. β_k the term slope coefficient pertains to all independent variables, ε term characterises the random error (residual) in the model.

4.2. Decision Tree

It is a fundamental algorithm in machine learning and data analysis used for classification and regression tasks. The DT consists of three nodes: root, internal, and leaf. The tree-like structure is used to represent the data, with core nodes representing decisions based on features, branches indicating the outcomes of those decisions, and leaf nodes representing class labels. The DT model results unveil the relative significance of the input parameters on the output parameter [33]. It is an example of a supervised machine learning algorithm that works by partitioning the input data into subsets based on the values of different features. The DT root node stores all input variables, and the internal node is associated with a decision function. A leaf node signifies the result of a specific vector input [34]. Pradhan [35] utilised a DT algorithm to create a spatial prediction model for a landslip susceptibility chart at Penang Hill, Malaysia. Figure 5 demonstrates the structure of the decision tree for the trained dataset.

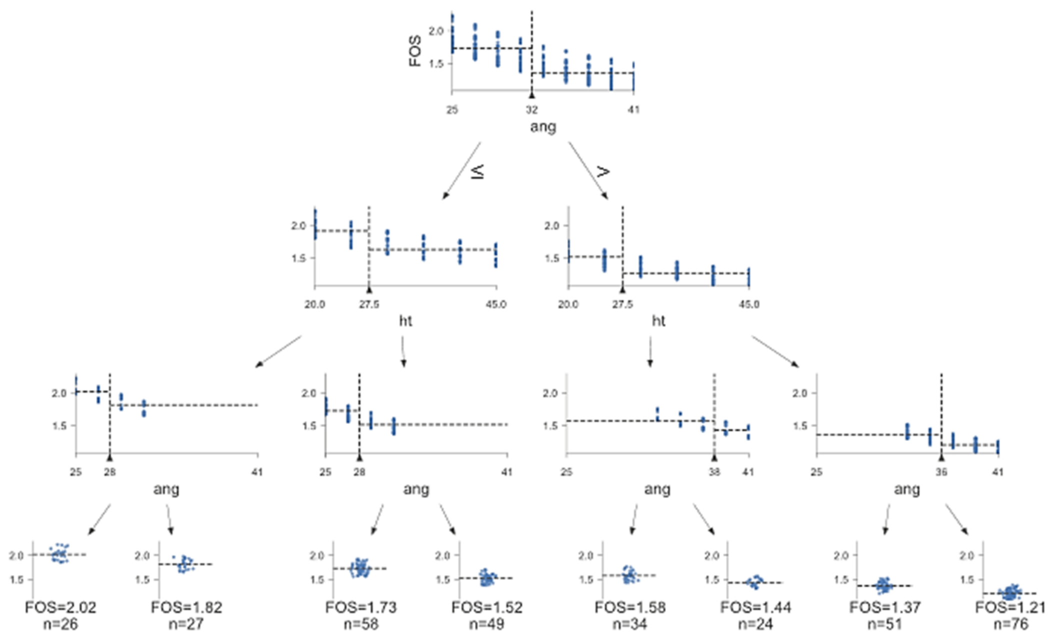

Figure 5. Decision tree for the tailings dam slope FoS prediction

4.3. Random Forest

RF is a widely used machine learning algorithm for classification and regression tasks. RF is an algorithm that constructs many decision trees using various subsets of the dataset. It then aggregates the forecasts of these trees by calculating their average. The aim of this approach is to improve the predictive accuracy of the dataset. Each sample has a group of sets which is trained individually and independently. During the process of training, just a random selection of features is used instead of using all the features. This is done to improve the variety across the decision trees [36]. The random forest model consists of many decision trees that make predictions in parallel and independently. The final forecast is determined by voting based on the outcomes of all the decision trees [37]. RF can mitigate the problem of overfitting by randomly selecting both samples and their features. It is particularly effective in dealing with high-dimensional data and have the ability to provide changeable significance scores during the decision-making process [38], [39]. RF is commonly employed in industries as black box models due to its ability to generate precise predictions across diverse datasets without requiring any preparation [40]. Figure 6 illustrates the technique of the RF algorithm used in the slope stability prediction.

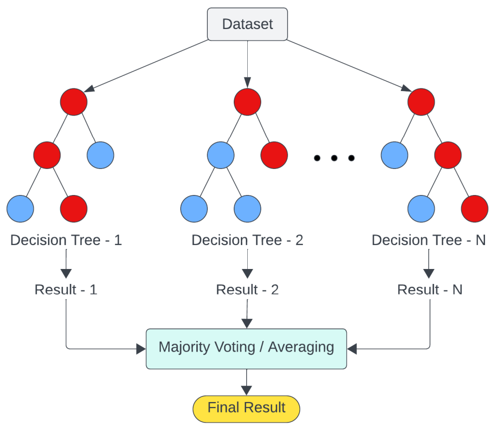

Figure 6. Illustration of random forest ML model

4.4. Support Vector Regression

Support vector machines (SVM) often employ machine learning models for forecasting decision boundaries and classifying data. SVM is useful for handling non-separable and high-dimensional data sets. Additionally, the related support vector regression (SVR) technique can be employed to address extrapolation and interpolation challenges. SVR is a machine-learning technique that is used for regression tasks. The SVR approach is based on the formulation of the Vapnik theory [41], [42], [43]. While the primary objective of basic regression is to minimise error rates, the main aim of SVR is to ensure that the error is contained within a predetermined threshold. It suggests that the SVR task aims to estimate the optimal value with a predefined margin [44]. It is used to predict a continuous output variable or dependent variable based on input features. SVR takes a different approach unlike conventional regression techniques, where a regression function that maintains a specific margin of error around the predicted values is found, rather than fitting the data exactly. It aims to find a hyperplane that optimally aligns with the data points within a continuous space. The procedure entails mapping input variables to a feature space within a high dimensional space, followed by the selection of the hyperplane that most accurately aligns with the data. From the scikit learn documentation [45], Figure 7 is an example of a hyperplane constructed for samples on the decision boundaries.

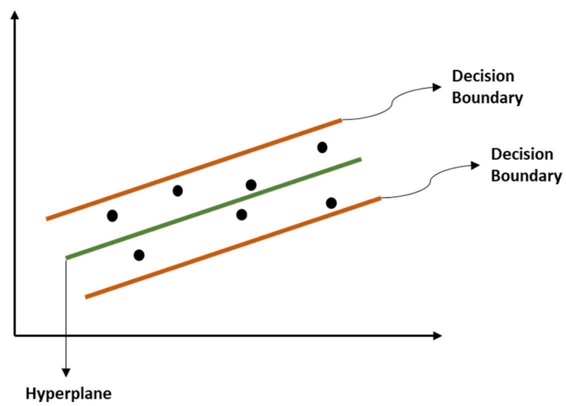

Figure 7. Basic visualisation of support vector regression

4.5. Xtreme Gradient Boosting

XGB is a powerful and widely used machine learning technique that comes under the gradient boosting method. XGB is designed to address the limitations of traditional gradient boosting and has gained popularity for its high performance and effectiveness across a variety of ML tasks, including classification, regression, and ranking problems [46]. XGBoost can generate accurate predictions faster than random forest and almost as well as deep neural [47]. The model is constructed using the gradient boosting framework, aggregating numerous weak decision trees to form a powerful ensemble model. It uses an approach to building decision trees, where it evaluates all possible splits and selects the one that results in the greatest reduction in the loss function. This approach leads to better and more informed tree structures [48]. Zhou et al. [49] approach an XGB to determine slope stability. Figure 8 shows the schematic illustration of the XGB model.

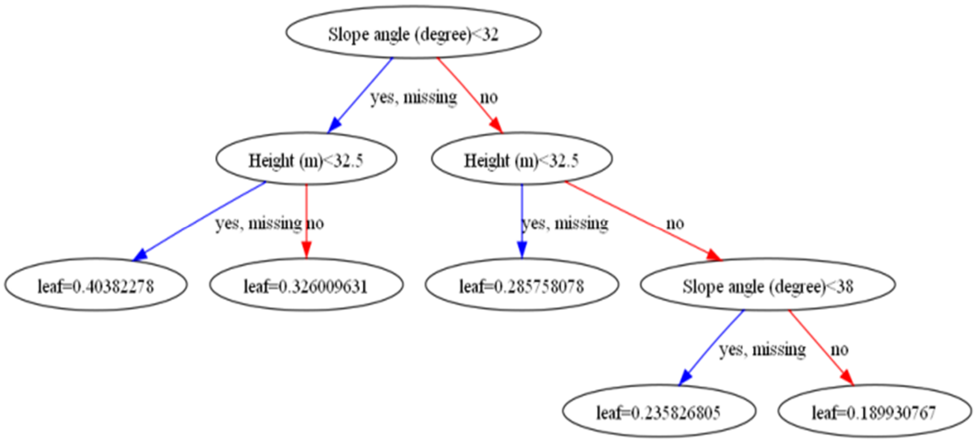

Figure 8. Schematic illustration of Xtreme Gradient Boosting model

4.6. Data Pre-processing

In this investigation, 767 numerical models were solved, and FoS of tailings dam slopes were calculated with respective geometry parameters and material strength. Numerical model datasets were used to establish the ML models as training and testing datasets. The number of sample data sets used in ML models is enough to generate a reliable model for the tailings dam stability assessment. Many researchers have used a lesser number of datasets to develop ML models for slope stability prediction [50], [51], [52], [53], [54]. Figure 9 illustrates the entire scheme of AI tool development using the slope stability datasets.

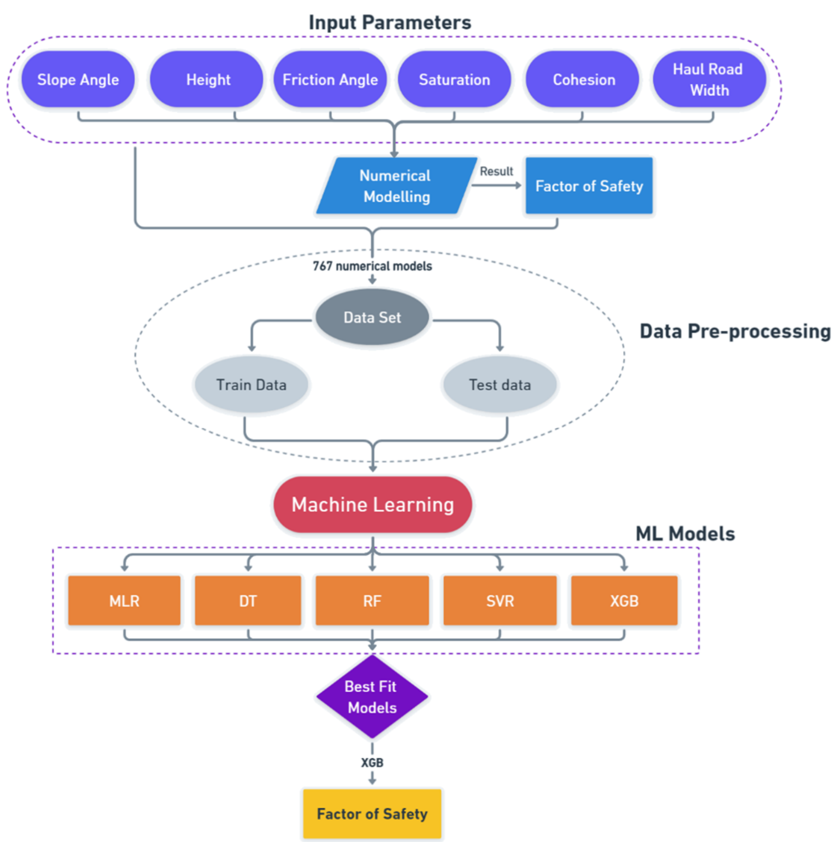

Figure 9. Workflow for pre-processing the datasets and AI tool development

Numerical modelling software is widely used in geotechnical engineering to simulate the behaviour of slopes and FoS calculations. A total 767 numerical models were solved for the tailings dam slope stability calculated using the finite difference solver in the Flac^{2D} software, with Mohr-Coulomb failure criteria. This study mainly focuses on the dam geometry parameters, and its effect was analysed. The data extraction process from the numerical models involves several vital points.

In numerical analysis, modelling input parameters play an essential role in the dam slope stability. The input parameters will be geometry, material properties, and loading conditions. The dam slope stability depends on the geometry of parameters and material shear strength properties. The outcome of dam stability will be the FoS. Therefore, we collect data from numerical modelling as input and output.

Numerical modelling is a powerful tool for slope FoS calculation, stress-strain and deformation analysis. This study calculates the tailings dam slope FoS using the shear strength reduction method. This investigation considers the tailings dam geometry parameters and material shear strength properties for the dam slope FoS calculation. These data sets were used in the ML model's training and testing.

767 numerical models were solved to obtain the slope FoS with different slope stability affecting parameters such as height, slope angle, haul road width, material properties, and saturation conditions. Table 2 lists the variation of the parameters in the numerical modelling used for the slope FoS calculation.

Table 2. Parameters used in the numerical modelling

S. no.	Parameters	Range
1	Height	20 - 55 m
2	Slope angle	25 - 41°
3	Haul road width	10 - 18 m
4	Cohesion	28000 - 36000 Pa
5	Friction angle	25 - 33°
6	Saturation of tailing material	0 - 0.8

Data sets are divided into a ratio of 4:1 for training and testing. The correlation between the parameters is shown in Figure 10, using a heatmap. A correlation matrix visualises data that identifies the features with the most vital relationship with the target feature. Each feature in a dataset is encoded as colours, which serve as indicators to researchers of the relationship between features.

5. Results and Discussion

5.1. Tailings Dam Slope Stability Analysis

In the numerical modelling, tailings dam slope FoS has been calculated using Mohr's-Coulomb failure criteria with input parameters such as density, cohesion, internal angle of friction, and saturation condition. Figure 11 shows the displacement vector of the dam slope under static conditions. Figure 12(a) and (b) show the model's simulation result, indicating a stable slope because the FoS is 1.45. This investigation considers the influence of height, slope angle, shear strength parameters, saturation, and haul road width.

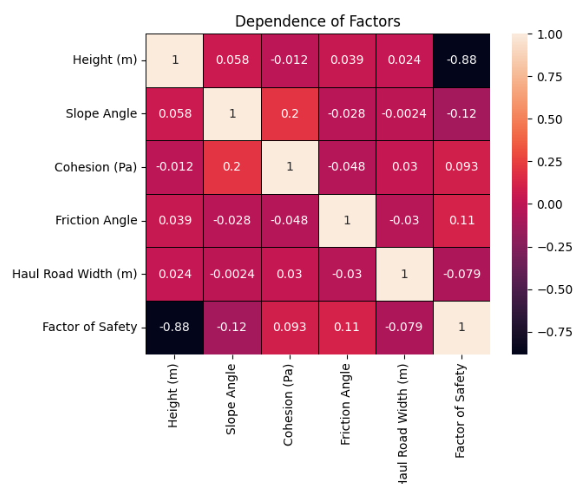

Figure 10. Heatmap showing the correlation of parameters

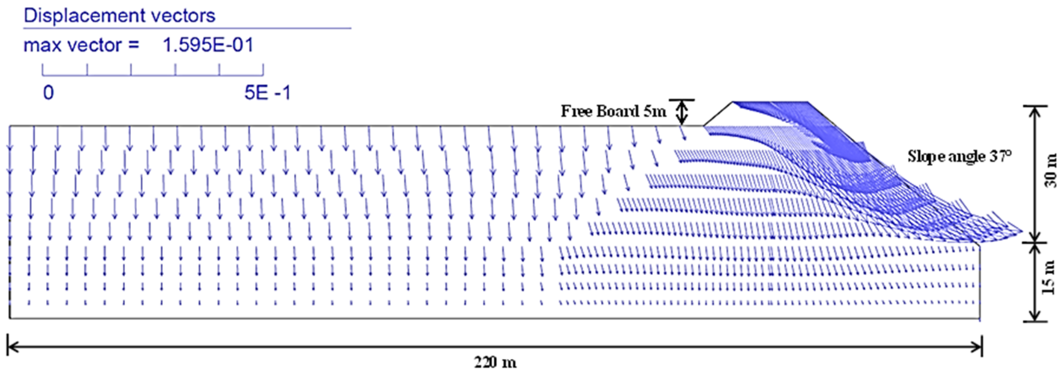

Figure 11. Numerical modelling illustrates the displacement vector of the tailings dam slope

Dam height (m)	Slope angle	Cohesion (Pa)	Friction angle	Haul road width (m)	Factor of safety	Horizontal displacement (cm)
30	37	35000	33	15	1.45	12

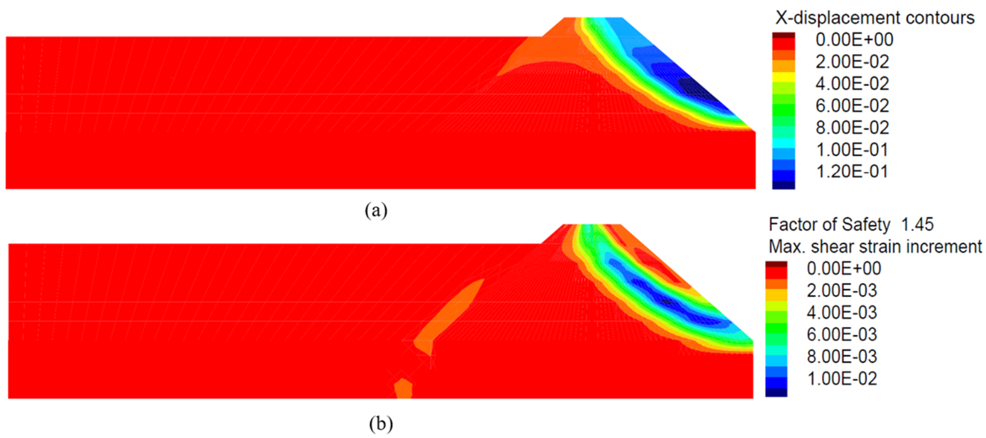

Figure 12. Numerical modelling results of tailings dam (a) slope horizontal displacement, and (b) maximum shear strain increment with slope factor of safety under gravity force

5.2. ML Model Efficiency

Five machine learning algorithms have been applied for slope stability prediction. The ML model efficiency was analysed based on the value of MSE, RMSE, MAE and R^2. ML model results are shown in Figure 13. Figure 14 shows the efficiency and accuracy of ML models.

A graph between predicted and measured values helps to visually assess how well the predicted values match the actual measured values.

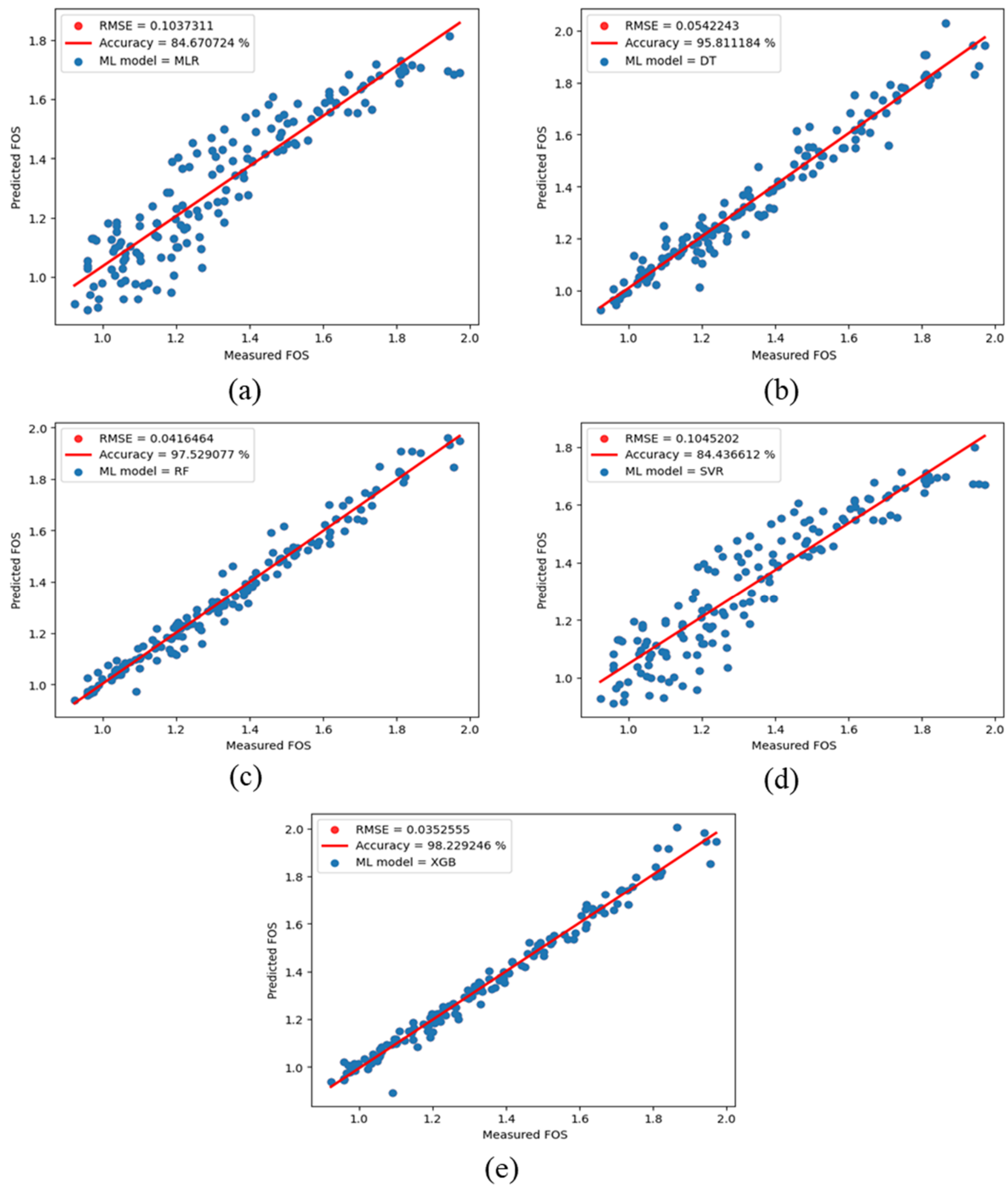

Figure 13. Charts for predicted and measured FoS results using machine learning (a) MLR Model, (b) DT model, (c) RF model, (d) SVR model, (e) XGB model accuracy and coefficient of determination

Ideally, the points on the graph should align along a diagonal line, indicating a strong positive correlation between the predicted and measured values. This diagonal line is called the regression line and if the points deviate significantly from the regression line, it suggests a discrepancy between the predicted and measured values, indicating potential inaccuracies or errors in the prediction model. From the graphs, it is verified that prediction models are working well, and there is a good consistency between the measured FoS values and the predicted FoS values. Table 3 lists the ranking of ML models based on MSE, RMSE, MAE and R^2. The XGB ML model performance is better than that of the other ML models. The hyperparameter optimisation process improved performance results by determining the most efficient parameters. The repetitive iterations necessary to train and evaluate models to determine the optimal values for the hyperparameters render this a complex task. Table 4 illustrates the default values of the parameters max_depth, n_estimators, gamma, and learning_rate, which have been tuned.

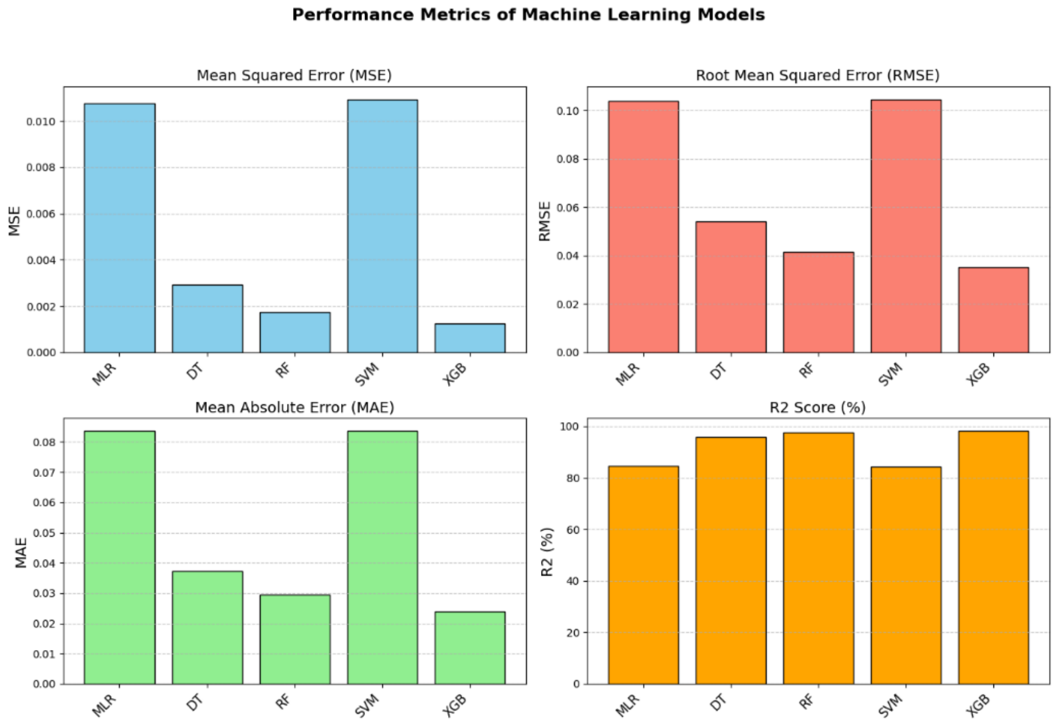

Figure 14. Comparative performance metrics of ML models

Table 3. Ranking of ML models

Model	MSE	RMSE	MAE	R^2	Rank
MLR	0.0107	0.1037	0.0835	84.6707	4
DT	0.0029	0.0542	0.0373	95.8111	3
RF	0.0017	0.0416	0.0295	97.5290	2
SVM	0.0109	0.1045	0.0836	84.4366	5
XGB	0.0012	0.0352	0.0239	98.2292	1

Table 4. Hyperparameter of the ML models

Algorithm	Hyper-Parameter	Value
MLR	-	-
RF	n_estimators	100
	max_depth	None
	min_samples_split	2
	min_samples_leaf	1
	bootstrap	True
SVR	C	1.0
	epsilon	0.1
	gamma	scale
	kernel	linear
DT	max_depth	None
	Min Samples Split	2
	Min Samples Leaf	1
	Criterion:	squared_error
XGB	n_estimators	1000
	learning_rate	None
	max_depth	4
	subsample	None
	colsample_bytree	None

5.3. AI User Interface for Tailings dam Slope Stability Prediction

A graphical user interface (GUI) was developed on the web page for the slope stability prediction, as seen in Figure 16. GUI shows the geometry parameters, material strength, and saturation as input values and FoS as output. Best fit ML model data is stored on the website with web security for the AI interface development. For GUI security, a unique ID and password was generated (Figure 15). This AI tool will require access to the internet. The developed AI user interface can be assessed through the internet, and slope stability can be predicted using a personal laptop and mobile (AI User Interface for Tailings dam Slope Stability Prediction). The FoS results can help determine a stable and unstable slope based on the dam slope. In the GUI background, the XGB ML algorithm was used for the slope stability prediction because this algorithm has higher efficiency than other ML algorithms in this study. AI tool results were compared with the numerical modelling results, and an absolute error of 0 – 3 % was obtained. Figure 17 depicts the FoS values calculated by numerical modelling and predicted by the AI tool, respectively.

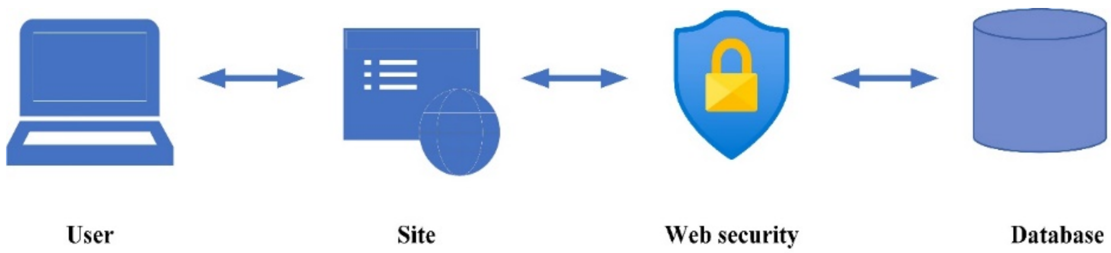

Figure 15. The flowchart shows the data storage on the webpage and user interface for FoS prediction

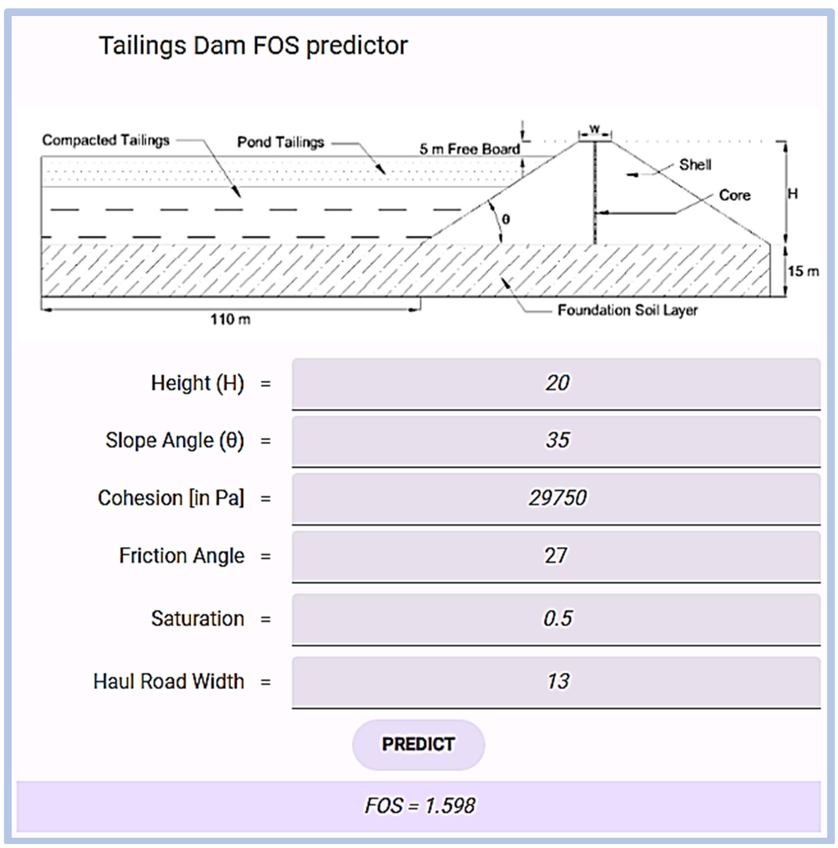

Figure 16. AI user interface for the tailings dam slope stability prediction

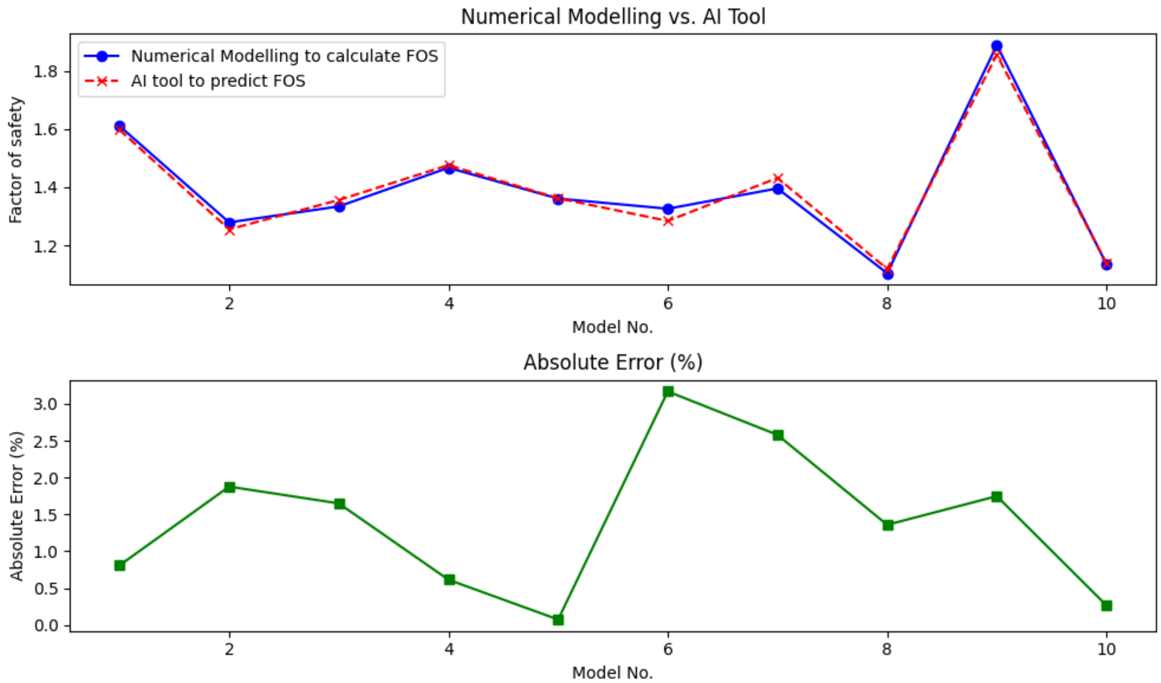

Figure 17. Graphs show the FoS results using modelling and AI tool with the absolute error

6. Conclusions

This study focuses on the tailings dam stability aspects, and the issues faced by geotechnical engineers were investigated. The issues governing the dam slope stability consist of high computational cost, time consumption, and the high economic value of the present tools. This study used numerical modelling and machine learning models (MLR, SVR, RF, DT, and XGB) to estimate the tailings dam stability. Based on the results, the following points emerge:

1. The results show that the FoS of the dam slope depends on the saturation, height, slope angle, haul road width, cohesion, and friction angle of the tailings dam.
2. Results of ML models indicate that ensemble learning models (RF and XGB) perform higher than ML models (MLR, SVR, DT). Finally, the best-fit ML model in this investigation is XGB for slope stability prediction based on accuracy and higher performance.
3. Developed trained ML models were further integrated with a GUI tool for the swift assessment of the dam slope stability. The developed GUI tool is user-friendly and does not require technical expertise to handle it.
4. The developed AI user interface can be assessed through the internet, and slope stability can be predicted using a personal laptop and mobile.
5. The developed AI tool will be helpful for initial level tailings dam slope stability analysis. However, other factors, such as rainfall and seismic loading, can be included in the developed GUI tool for future work.

References

[1]. Wang, K., Yang, P., Yu, G., Yang, C., & Zhu, L. (2020). 3D numerical modelling of tailings dam breach run out flow over complex terrain: A multidisciplinary procedure. *Water, 12(9),* 2538.

[2]. Azam, S., & Li, Q. (2010). Tailings dam failures: a review of the last one hundred years. *Geotechnical news, 28(4),* 50-54.

[3]. Kossoff, D., Dubbin, W. E., Alfredsson, M., Edwards, S. J., Macklin, M. G., & Hudson-Edwards, K. A. (2014). Mine tailings dams: Characteristics, failure, environmental impacts, and remediation. *Applied geochemistry, 51,* 229-245.

[4]. Islam, K., & Murakami, S. (2021). Global-scale impact analysis of mine tailings dam failures: 1915–2020. *Global Environmental Change, 70,* 102361.

[5]. Zhang, C., Chai, J., Cao, J., Xu, Z., Qin, Y., & Lv, Z. (2020). Numerical simulation of seepage and stability of tailings dams: A case study in Lixi, China. *Water, 12(3),* 742.

[6]. Xu, B., & Wang, Y. (2015). Stability analysis of the Lingshan gold mine tailings dam under conditions of a raised dam height. *Bulletin of Engineering Geology and the Environment, 74,* 151-161.

[7]. Ozcan, N. T., Ulusay, R., & Isik, N. S. (2013). A study on geotechnical characterization and stability of downstream slope of a tailings dam to improve its storage capacity (Turkey). *Environmental Earth Sciences, 69,* 1871-1890.

[8]. Alsharedah, Y. A., El Naggar, M. H., & Ahmed, A. (2023). Improving Tailings Dam Safety via Soil Treatment. *Sustainability, 15(21),* 15276.

[9]. Ledesma, O., Sfriso, A., & Manzanal, D. (2022). Procedure for assessing the liquefaction vulnerability of tailings dams. *Computers and Geotechnics, 144,* 104632.

[10]. Van Niekerk, H. J., & Viljoen, M. J. (2005). Causes and consequences of the Merriespruit and other tailings-dam failures. *Land degradation & development, 16(2),* 201-212.

[11]. Sadrekarimi, A., & Riveros, G. A. (2020). Static liquefaction analysis of the Fundão dam failure. *Geotechnical and Geological Engineering, 38,* 6431-6446.

[12]. Mayne, P., & Sharp, J. (2021). Screening for flow liquefaction for tailings and natural soils by CPTU. In *Proceedings of the 20th international conference on soil mechanics and geotechnical engineering* (pp. 459-464).

[13]. Cambridge, M., & Shaw, D. (2019). Preliminary reflections on the failure of the Brumadinho tailings dam in January 2019. *Dams and Reservoirs, 29(3),* 113-123.

[14]. Sitharam, T. G., & Hegde, A. (2017). Stability analysis of rock-fill tailing dam: an Indian case study. *International Journal of Geotechnical Engineering, 11(4),* 332-342.

[15]. Pacheco, F., Hermosilla, G., Piña, O., Villavicencio, G., Allende-Cid, H., Palma, J., ... & Novoa, G. (2022). Generation of synthetic data for the analysis of the physical stability of tailing dams through artificial intelligence. *Mathematics, 10(23),* 4396.

[16]. Lyu, Z., Chai, J., Xu, Z., Qin, Y., & Cao, J. (2019). A comprehensive review on reasons for tailings dam failures based on case history. *Advances in Civil Engineering,* 2019(1), 4159306.

[17]. Chakraborty, D., & Choudhury, D. (2009). Investigation of the behavior of tailings earthen dam under seismic conditions. *American Journal of Engineering and Applied Sciences, 2(3),* 559-564.

[18]. Singh, R., Umrao, R. K., & Singh, T. N. (2017). Hill slope stability analysis using two and three dimensions analysis: A comparative study. *Journal of the Geological Society of India, 89,* 295-302.

[19]. Latha, G. M., & Garaga, A. (2010). Seismic stability analysis of a Himalayan rock slope. *Rock Mechanics and Rock Engineering, 43,* 831-843.

[20]. Rai, R., Kalita, S., Gupta, T., & K Shrivastva, B. (2012). Sensitivity analysis of internal dragline dump stability: finite element analysis. *Geotechnical and Geological Engineering, 30,* 1397-1404.

[21]. Koner, R. (2021). Estimation of optimum geometric configuration of mine dumps in Wardha valley coalfields in India: A case study. *Journal of Mining and Environment, 12(4),* 907-927.

[22]. Chand, K., & Koner, R. (2024). Failure zone identification and slope stability analysis of mine dump based on realistic 3D numerical modeling. *Geotechnical and Geological Engineering, 42(1),* 543-560.

[23]. Koner, R., & Chakravarty, D. (2016). Numerical analysis of rainfall effects in external overburden dump. *International Journal of Mining Science and Technology, 26(5),* 825-831.

[24]. Lin, S., Zheng, H., Han, C., Han, B., & Li, W. (2021). Evaluation and prediction of slope stability using machine learning approaches. *Frontiers of Structural and Civil Engineering, 15(4),* 821-833.

[25]. Santos, A. E. M., Lana, M. S., & Pereira, T. M. (2022). Evaluation of machine learning methods for rock mass classification. *Neural Computing and Applications, 34(6),* 4633-4642.

[26]. Yilmaz, I., & Yuksek, A. G. (2008). An example of artificial neural network (ANN) application for indirect estimation of rock parameters. *Rock Mechanics and Rock Engineering, 41(5),* 781.

[27]. Tabrizi, S. S., & Sancar, N. (2017). Prediction of Body Mass Index: A comparative study of multiple linear regression, ANN and ANFIS models. *Procedia computer science, 120,* 394-401.

[28]. Khademi, F., Jamal, S. M., Deshpande, N., & Londhe, S. (2016). Predicting strength of recycled aggregate concrete using artificial neural network, adaptive neuro-fuzzy inference system and multiple linear regression. *International Journal of Sustainable Built Environment, 5(2),* 355-369.

[29]. Erzin, Y., & Cetin, T. (2013). The prediction of the critical factor of safety of homogeneous finite slopes using neural networks and multiple regressions. *Computers & Geosciences, 51,* 305-313.

[30]. Pradhan, B. (2010). Landslide susceptibility mapping of a catchment area using frequency ratio, fuzzy logic and multivariate logistic regression approaches. *Journal of the Indian Society of Remote Sensing, 38,* 301-320.

[31]. Pradhan, B. (2010). Remote sensing and GIS-based landslide hazard analysis and cross-validation using multivariate logistic regression model on three test areas in Malaysia. *Advances in space research, 45(10),* 1244-1256.

[32]. Moayedi, H., Tien Bui, D., Kalantar, B., & Kok Foong, L. (2019). Machine-learning-based classification approaches toward recognizing slope stability failure. *Applied Sciences, 9(21),* 4638.

[33]. Kheir, R. B., Greve, M. H., Abdallah, C., & Dalgaard, T. (2010). Spatial soil zinc content distribution from terrain parameters: A GIS-based decision-tree model in Lebanon. *Environmental Pollution, 158(2),* 520-528.

[34]. Tien Bui, D., Pradhan, B., Lofman, O., & Revhaug, I. (2012). Landslide susceptibility assessment in vietnam using support vector machines, decision tree, and Naive Bayes Models. *Mathematical problems in Engineering, 2012(1),* 974638.

[35]. Pradhan, B. (2013). A comparative study on the predictive ability of the decision tree, support vector machine and neuro-fuzzy models in landslide susceptibility mapping using GIS. *Computers & Geosciences, 51,* 350-365.

[36]. Paudel, U., Oguchi, T., & Hayakawa, Y. (2016). Multi-resolution landslide susceptibility analysis using a DEM and random forest. *International Journal of Geosciences, 7(5),* 726-743.

[37]. Xie, H., Dong, J., Deng, Y., & Dai, Y. (2022). Prediction model of the slope angle of rocky slope stability based on random forest algorithm. *Mathematical Problems in Engineering, 2022(1),* 9441411.

[38]. Breiman, L. (2001). Random forests. *Machine learning, 45,* 5-32.

[39]. Zhou, J., Li, X., & Shi, X. (2012). Long-term prediction model of rockburst in underground openings using heuristic algorithms and support vector machines. *Safety science, 50(4),* 629-644.

[40]. Piryonesi, S. M., & El-Diraby, T. E. (2020). Role of data analytics in infrastructure asset management: Overcoming data size and quality problems. *Journal of Transportation Engineering, Part B: Pavements, 146(2),* 04020022.

[41]. Drucker, H., Burges, C. J., Kaufman, L., Smola, A., & Vapnik, V. (1996). Support vector regression machines. Advances in neural information processing systems, 9.

[42]. Vapnik, V., Golowich, S., & Smola, A. (1996). Support vector method for function approximation, regression estimation and signal processing. *Advances in neural information processing systems,* 9.

[43]. Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine learning, 20,* 273-297.

[44]. Yahyaoui, N., Neji, M., Kallel, M., Wali, A., & Hajji, S. (2023). A comparative approach of ML algorithms to rank irrigation water quality: case of Oriental-Coast shallow aquifer in Cap-Bon, northeastern of Tunisia. *Modeling Earth Systems and Environment, 9(3),* 3733-3746.

[45]. Pedregosa, F. (2011). Scikit-learn: Machine learning in python Fabian. *Journal of machine learning research, 12,* 2825.

[46]. Bentéjac, C., Csörgő, A., & Martínez-Muñoz, G. (2021). A comparative analysis of gradient boosting algorithms. *Artificial Intelligence Review, 54,* 1937-1967.

[47]. Sheridan, R. P., Wang, W. M., Liaw, A., Ma, J., & Gifford, E. M. (2016). Extreme gradient boosting as a method for quantitative structure–activity relationships. *Journal of chemical information and modeling, 56(12),* 2353-2360.

[48]. Chen, T., & Guestrin, C. (2016, August). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (pp. 785-794).

[49]. Zhou, J., Li, E., Yang, S., Wang, M., Shi, X., Yao, S., & Mitri, H. S. (2019). Slope stability prediction for circular mode failure using gradient boosting machine approach based on an updated database of case histories. *Safety Science, 118,* 505-518.

[50]. Dehghan, S., Sattari, G. H., Chelgani, S. C., & Aliabadi, M. A. (2010). Prediction of uniaxial compressive strength and modulus of elasticity for Travertine samples using regression and artificial neural networks. *Mining Science and Technology (China), 20(1),* 41-46.

[51]. Monjezi, M., Hasanipanah, M., & Khandelwal, M. (2013). Evaluation and prediction of blast-induced ground vibration at Shur River Dam, Iran, by artificial neural network. *Neural Computing and Applications, 22,* 1637-1643.

[52]. Ebrahimi, E., Monjezi, M., Khalesi, M. R., & Armaghani, D. J. (2016). Prediction and optimization of back-break and rock fragmentation using an artificial neural network and a bee colony algorithm. *Bulletin of Engineering Geology and the Environment, 75,* 27-36.

[53]. Akinwekomi, A. D., & Lawal, A. I. (2021). Neural network-based model for predicting particle size of AZ61 powder during high-energy mechanical milling. *Neural Computing and Applications, 33,* 17611-17619.

[54]. Aladejare, A. E., Ozoji, T., Lawal, A. I., & Zhang, Z. (2022). Soft computing-based models for predicting the characteristic impedance of igneous rock from their physico-mechanical properties. *Rock Mechanics and Rock Engineering, 55(7),* 4291-4304.

ابزار هوش مصنوعی برای پیش‌بینی پایداری شیب سد باطله معدن

کاپور چاند، ود کومار، پریانشو راج، نیکیتا شارما، آمیت کومار مانکار و راداکانتا کونر*

گروه مهندسی معدن، موسسه فناوری هند (مدرسه معادن هند)، دانباد ۸۲۶۰۰۴، جارکند، هند

ارسال ۲۰۲۴/۰۵/۲۹، پذیرش ۲۰۲۴/۰۸/۰۴

* نویسنده مسئول مکاتبات: rkoner@iitism.ac.in

چکیده:

خرابی سدهای باطله یکی از مسائل مهم در صنعت معدن است زیرا به شدت بر محیط زیست و زندگی تأثیر می‌گذارد. یکی از دلایل اصلی شکست سدهای باطله، رسوب بی‌برنامه باطله و افزایش اشباع ناشی از حوادث بارندگی است. این مطالعه با استفاده از تکنیک‌های مدل‌سازی عددی و هوش مصنوعی (مانند MLR، SVR، DT، RF و XGB) با هدف پیش‌بینی پایداری شیب سدهای باطله برای جلوگیری از شکست انجام شده است. پایداری سدهای باطله با استفاده از روش تفاضل محدود (FDM)، که ضریب ایمنی (FoS) را با استفاده از تکنیک کاهش مقاومت برشی (SSR) محاسبه می‌کند، تجزیه و تحلیل می‌شود. این تحقیق عمدتاً بر پارامترهای ژئوتکنیکی و هندسی سد باطله مانند چگالی، چسبندگی، زاویه اصطکاک، اشباع، ارتفاع خاکریزی، زاویه شیب و عرض جاده تمرکز دارد. از نتایج مدل‌سازی عددی برای توسعه مدل‌های ML و پیش‌بینی پایداری شیب استفاده شده است. کارایی مدل‌های ML بر اساس R2 و ریشه میانگین مربعات خطا (RMSE)، میانگین مربعات خطا (MSE) و میانگین خطای مطلق (MAE) تجزیه و تحلیل شد. الگوریتم XGB ثابت کرد که موثرترین است زیرا بالاترین دقت و کمترین مقدار RMSE را در مقایسه با سایر مدل‌های ML ارائه می‌دهد. ابزار هوش مصنوعی بر اساس نتایج مدل ML برای پیش‌بینی پایداری شیب سد توسعه داده شد. ابزار هوش مصنوعی توسعه یافته به درک نقش پارامترهای اشباع و هندسه در پایداری خاکریز در سطح اولیه تحقیقات کمک می‌کند.

کلمات کلیدی: پایداری سد باطله، مدلسازی عددی، ضریب ایمنی، یادگیری ماشین.