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Predictive modelling of slope reliability for a Victorian open pit mine using numerical and artificial intelligence techniques

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Abstract

In mining operations, ensuring the stability of slopes is paramount for safety and operational efficiency. This study focuses on predicting slope reliability in open pit mines, utilising a combination of numerical modelling techniques and artificial intelligence (AI). The case study centres on a lignite mine in the Latrobe Valley, Victoria, incorporating key geotechnical parameters such as overburden thickness, lignite strength properties, and slope angle to develop predictive models. Using approximately 30 datasets, both linear and non-linear AI models were developed to generate predictive equations for slope reliability. The linear model achieved a coefficient of determination (R^2) of 0.832 for the training dataset and 0.762 for the test dataset, while the non-linear model demonstrated even higher precision with R^2 values of 0.963 and 0.929, respectively. This study underscores the critical influence of slope angle and cohesion on slope reliability, offering valuable insights for the management of open pit mining operations. By refining predictive modelling techniques, this research contributes to enhanced safety protocols and operational effectiveness in the mining industry.

Keywords: *Factor of Safety, artificial intelligence, open pit mine, Victoria*

1 Introduction

In modern mining operations, ensuring the safety and efficiency of open pit mines stands as a paramount concern. Central to this endeavour is the calculation of the Factor of Safety (FoS), a critical measure of slope stability that directly impacts operational integrity and personnel safety. Over the years, researchers and industry professionals have employed a diverse array of methodologies to tackle this challenge, ranging from traditional numerical modelling techniques to cutting-edge AI approaches (Gupta et al. 2021; Bui et al. 2020; Nguyen et al. 2023).

Numerical modelling techniques have long been a cornerstone of slope stability analysis in open pit mines (Chiwaye & Stacey 2010; Gupta et al. 2021). Methods such as finite element method (Bar et al. 2019; Dehghan & Khodaei 2022) and distinct element method (Xu et al. 2016; Zhao et al. 2023) have enabled engineers to simulate the complex interactions between geological structures, rock masses, and applied stresses. These models take into account a multitude of factors, including geological discontinuities, rock strength properties, and pore pressure distributions, to provide estimations of FoS under varying conditions. While numerical modelling offers detailed insights into slope behaviour, its reliance on accurate input parameters and computational resources has spurred interest in complementary AI-based approaches. These AI methods can leverage large datasets and uncover complex patterns without the same level of dependency on precise input data, making them a valuable tool alongside traditional numerical technique.

AI, particularly machine learning algorithms, has emerged as a powerful tool for predictive modelling in open pit mining. Linear regression (Kirin et al. 2021), artificial neural networks (Ferentinou & Fakir 2018), support vector machines (Li et al. 2017), and other AI techniques excel in handling complex, non-linear relationships within datasets, making them well-suited for FoS calculation By analysing large volumes of heterogeneous

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data, including geological surveys, geotechnical tests, and operational records, AI models can identify hidden patterns and correlations that traditional methods might overlook. Moreover, AI's ability to adapt and learn from new data over time enhances the robustness and accuracy of predictive models.

Key parameters influencing FoS in open pit mines have been extensively studied and documented. Geological and geotechnical characteristics, such as coal type (Kaihuan & Fuchuan 2012), structure (Sakurai & Farazmand 2010; Baumgartl et al. 2023), and weathering (Rezaei et al. 2024) exert profound effects on slope stability by influencing factors like block size distribution (Guo et al. 2024) and joint spacing (Cao et al. 2023). Geotechnical properties including cohesion, friction angle, and Young's modulus directly dictate the mechanical behaviour of rocks and soils under loading conditions (Singh et al. 2005, Daghistani et al. 2023; Baghbani et al. 2023). Operational factors such as blasting activities (Sari et al. 2014), excavation techniques (Bazaluk et al. 2023), and waste disposal practices (Li et al. 2024) introduce dynamic changes to slope geometry and material properties, necessitating continuous monitoring and risk assessment (Chandarana et al. 2016; Baghbani et al. 2024).

Numerous case studies have contributed to the body of knowledge surrounding FoS calculation in open pit mines. These studies have explored the efficacy of different modelling approaches, highlighted the significance of key parameters, and provided practical insights for mine design and management. For instance, the work of Bui et al. (2020) demonstrated the potential of machine learning models to outperform traditional numerical methods in predicting FoS, while Wang et al. (2023) highlighted the benefits of integrating AI with traditional geotechnical approaches. However, the unique geological and operational characteristics of each mining site necessitate tailored solutions and methodologies. The Victorian open pit mine serves as a pertinent case study in this regard, offering an opportunity to apply and validate predictive models in a real-world setting.

By using 108 datasets encompassing a wide range of parameters, including overburden thickness, coal strength properties, and slope geometry, this study aims to develop accurate and robust predictive models for the FoS at the Yallourn open pit mine. The integration of numerical modelling techniques and AI methodologies holds the promise of enhancing our understanding of slope stability dynamics and facilitating informed decision-making in open pit mining operations. Ultimately, by elucidating predictive models and identifying key contributing factors, this research endeavours to bolster safety protocols and operational efficiency in the challenging environment of open pit mines.

2 Methodology

2.1 Numerical modelling

To establish a numerical model for the Victoria mine, the dimension of a representative cross-section from a Latrobe Valley mine was considered as depicted in Figure 1. The stability analysis in this study focuses on the coal slope, and the overburden material is treated as an in situ layer rather than an engineered cap. The material properties of coal, sourced from tests conducted at Federation University, were integrated into the model, adhering to the parameters delineated in Tables 1 and 2. Geo Studio software, specifically Slope/w, was employed for model construction.

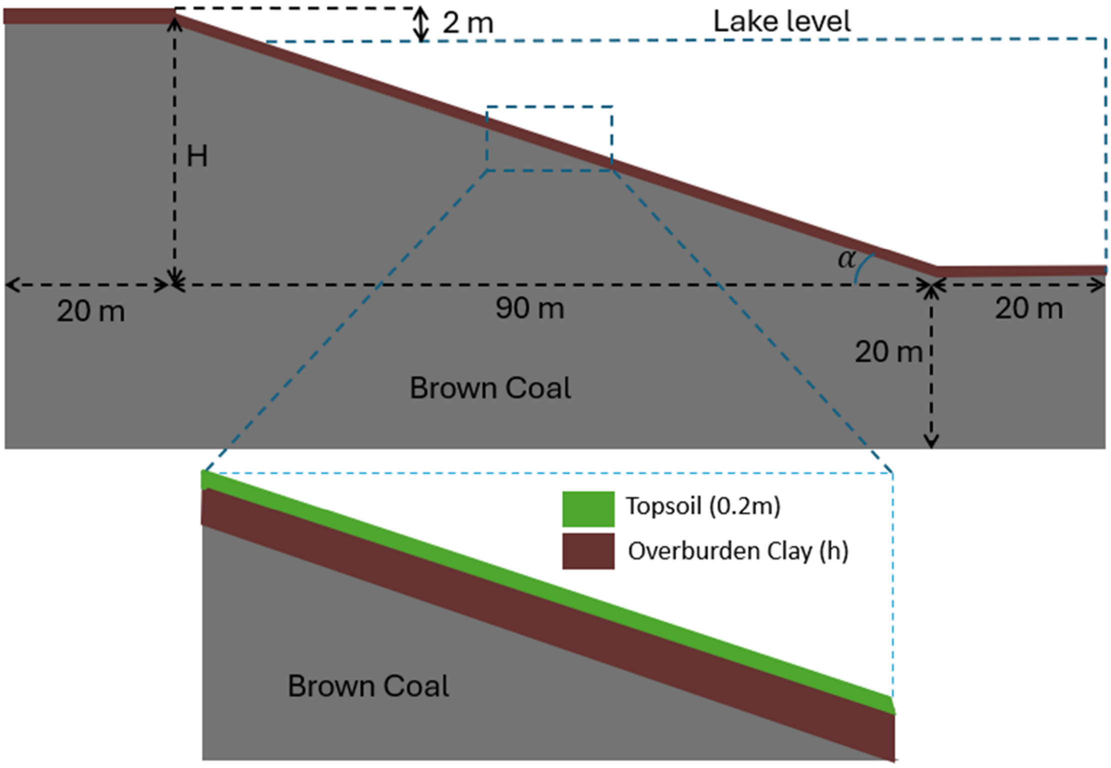

Figure 1 Geometry of cross-section modelled for the numerical modelling

In the evaluation of FoS within open pit mines, key input parameters for numerical modelling include overburden thickness (1, 2 and 4 m), overburden cohesion (0, 5 and 10 kPa), overburden friction angle (10, 20 and 30˚), and slope angle (10, 15, 20 and 25˚). These parameters collectively influence slope stability and the predictive accuracy of numerical models by capturing variations in material properties, geometric configurations, and external loading conditions. By systematically varying these parameters within their defined ranges, numerical simulations can simulate a wide array of geological and operational scenarios encountered in open pit mining operations, facilitating informed decision-making processes related to mine design, operational planning, and safety protocols.

Table 1 Used variables in modelling for overburden and slope

Parameters	Overburden thickness, h (m)	Overburden cohesion, c (kPa)	Overburden friction angle, φ (°)	Slope angle, α (°)
Values	1, 2, 4	0, 5, 10	10, 20, 30	10, 15, 20, 25

Furthermore, Table 2 focuses on the parameters specific to brown coal, listing a unit weight (γ) of 1200 kg/m^3, drained cohesion (c') of 10 kPa, and an undrained friction angle (φ) of 10°. These values are essential for understanding the mechanical behaviour and stability of the brown coal layer, providing a basis for accurate geotechnical modelling.

Table 2 Used variables in modelling for lignite

Parameters	Unit weight, γ (kg/m^3)	Drained cohesion, c (kPa)	Undrained friction angle, φ (°)
Values	1200	10	10

2.2 Artificial intelligence and statistical modelling

2.2.1 Linear normalisation

In this study, linear normalisation was used to reduce the error of units in the models. Linear normalisation, also known as min–max scaling, is a data preprocessing technique used to rescale numerical features to a specific range, typically between 0 and 1. This normalisation method involves transforming the original values of a feature by subtracting the minimum value and then dividing by the range (the maximum value minus the minimum value). By doing so, the entire range of values for a particular feature is compressed or stretched to fit within the 0 to 1 interval, ensuring consistency in scale across different features. Linear normalisation is particularly useful when the original data spans different scales or when algorithms or models require input features to be on a similar scale to prevent certain features from dominating others during the modelling process. However, it's important to note that linear normalisation does not change the distribution or shape of the data; it simply re-scales it linearly.

2.2.2 Multiple linear regression

Multiple linear regression (MLR) is a powerful statistical technique used to analyse the relationship between multiple independent variables and a single dependent variable. In essence, it extends the simple linear regression model to accommodate multiple predictors.

MLR is widely used in various fields such as economics, finance, and social sciences for predictive modelling and hypothesis testing. It allows researchers to assess the individual contributions of multiple predictors to the variation in the dependent variable, while controlling for the effects of other variables. Additionally, MLR provides valuable insights into the strength and direction of the relationships between variables, helping to identify significant factors driving the phenomenon under study. However, it's important to note that MLR assumes certain underlying assumptions such as linearity, independence of errors, constant variance, and normality of residuals, which should be carefully checked before interpreting the results.

2.2.3 Genetic programming

Genetic programming (GP) is a powerful machine learning technique inspired by the principles of natural selection and genetics (Brameier & Banzhaf 2007). Unlike traditional machine learning algorithms that rely on explicit programming, GP evolves computer programs to solve complex problems. At its core, GP treats programs as individuals within a population, subjecting them to genetic operators such as mutation, crossover, and selection to improve their performance over successive generations.

In GP, each program is represented as a tree structure, where each node in the tree corresponds to an operation or a terminal value. Mathematically, we can represent a program P as a syntax tree T_P. The tree is composed of nodes and edges, where nodes represent operations or terminal values, and edges represent the flow of computation. For example, in a symbolic regression task, each node might represent an arithmetic operation (e.g. addition, subtraction, multiplication) or a mathematical function (e.g. sine, cosine) (Sette & Boullart 2001).

GP offers several notable benefits in the realm of machine learning and optimisation. One significant advantage lies in its ability to handle complex, non-linear problems without requiring explicit problem-specific knowledge or assumptions. GP's evolutionary approach enables the exploration of diverse solution spaces, allowing it to discover novel and often unexpected solutions that may elude traditional algorithmic approaches. Moreover, GP's flexibility in representing solutions as tree structures facilitates the incorporation of domain-specific constraints and prior knowledge, enhancing its adaptability to various real-world applications (Nguyen et al. 2023).

2.2.4 Training and testing databases

In the process of building and evaluating machine learning and statistical models, it's important to split the available data into training and testing databases. In this study, with a dataset comprising 108 data points, 20% of the data was allocated for testing purposes, while the remaining 80% was designated for training the model. This division ensures that the model is trained on a sufficiently large dataset to learn patterns and relationships within the data while also reserving a separate portion for evaluation to assess the model’s performance on unseen data. Importantly, the selection of instances for both training and testing databases was conducted randomly to avoid any biases in the model’s learning process and to ensure representative samples from the overall dataset. This random selection helps to create robust models that can generalise well to unseen data, ultimately enhancing the reliability and effectiveness of the machine learning algorithms employed.

2.3 Feature importance

Feature importance is a technique used to identify and quantify the contribution of each input variable in a predictive model. It helps in understanding which features have the most influence on the model’s predictions, thereby providing insights into the underlying patterns and relationships in the data. Feature importance can be generated through various methods depending on the type of model used. For linear models like MLR, feature importance can be derived directly from the absolute values of the model’s coefficients, as they indicate the strength of each feature’s impact on the outcome. In more complex, non-linear models such as those created using GP, feature importance can be assessed by examining the coefficients or contributions of each feature within the model’s equation. By normalising these values, a comparative measure of importance for each feature can be created. Visualising feature importance through bar plots provides a clear and intuitive way to interpret and communicate these insights, helping in feature selection and model refinement processes.

3 Results

3.1 Numerical modelling

To investigate the effect of various parameters on the FoS and the associated failure mechanisms, 108 different models were conducted using GeoStudio software. The parameters studied included the slope angle of the lignite open pit, the friction angle and cohesion of the overburden soil, and the thickness of the overburden soil. The failure mechanism was modelled using the Mohr–Coulomb failure criterion. Figure 2 illustrates the impact of these four factors.

The results indicate that the stability outcomes investigated in this study focus on the overburden slope, rather than the coal slope, to clarify the scope of the analysis. It is important to exercise caution when interpreting the relationship between slope angle and stability, particularly in the context of coal slopes. While the findings suggest that the FoS decreases as the slope of the overburden increases, this may not always hold true for coal slopes, where factors such as underlying geology, groundwater conditions, and structural feature orientation may play a significant role. For example, a steeper coal batter could provide greater stability if the underlying geology is dipping into the open cut.

The analysis revealed that increasing the cohesion and friction angle of the overburden soil leads to a higher FoS, as these properties enhance the shear strength of the material. However, as the thickness of the overburden soil increases, the FoS decreases. This is attributed to the shift in the failure plane, which transitions from a deep failure to a shallow failure within the overburden layer. Given these findings, the limitations of the study should be acknowledged, and the conclusions should focus on the specific outcomes related to the overburden slope rather than making general statements about slope stability in coal mines. The aim of this research is to demonstrate the AI process being tested and its application in predicting stability, with the findings specifically related to the overburden conditions at the site under investigation.

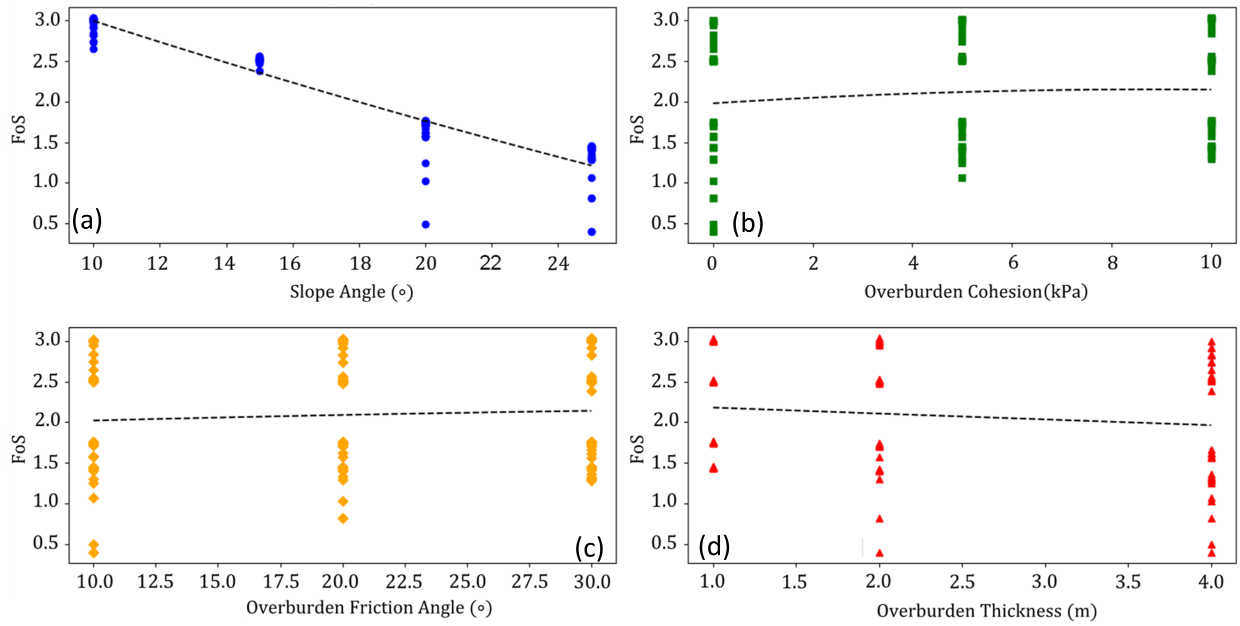

Figure 2 Effect of different parameters on Factor of Safety (FoS)

3.2 Database preparation

The statistical information of the database, as shown in Table 3, encompasses 108 observations for FoS, slope angle, cohesion, friction angle, and thickness. The FoS values range from 0.397 to 3.036, with an average of 2.084 and a standard deviation of 0.709. Slope values range from 10.000 to 25.000˚, with a mean of 17.500˚ and a standard deviation of 5.616, reflecting significant spread. Cohesion varies between 0.000 kPa and 10.000 kPa, averaging 5.000 kPa with a standard deviation of 4.102. Friction values span from 10.000˚ to 30.000°, with a mean of 20.000˚ and a standard deviation of 8.203. Lastly, thickness ranges from 1.000 m to 4.000 m, with an average of 2.333 m and a standard deviation of 1.253.

Table 3 Statistical information of database

Variable	Observations	Minimum	Maximum	Mean	Standard deviation
FoS	108	0.397	3.036	2.084	0.709
Slope (°)	108	10.000	25.000	17.500	5.616
Cohesion (kPa)	108	0.000	10.000	5.000	4.102
Friction angle (°)	108	10.000	30.000	20.000	8.203
Thickness (m)	108	1.000	4.000	2.333	1.253

3.2.1 Training and testing databases

Tables 4 and 5 provide statistical information for the training and testing databases. The statistical information of both the training and testing databases exhibits close similarities across variables. This similarity suggests that the distributions of the datasets are comparable, with similar ranges, means, and standard deviations for corresponding variables. Such congruence between training and testing datasets can positively impact the accuracy of prediction models. When the testing dataset closely resembles the training dataset, it enhances the model's ability to generalise effectively to unseen data. The similarity in statistical characteristics indicates that the model is being tested on data that is representative of what it was trained on, potentially leading to more reliable and robust predictions. This alignment between training and testing datasets underscores the importance of dataset selection and quality in improving the accuracy and generalizability of predictive models.

Table 4 Statistical information of training database

Variable	Observations	Minimum	Maximum	Mean	Standard deviation
FoS	86	0.397	3.036	2.081	0.694
Slope (°)	86	10.000	25.000	17.674	5.568
Cohesion (kPa)	86	0.000	10.000	5.291	4.084
Friction angle (°)	86	10.000	30.000	19.884	8.188
Thickness (m)	86	1.000	4.000	2.209	1.199

Table 5 Statistical information of testing database

Variable	Observations	Minimum	Maximum	Mean	Standard deviation
FoS	22	0.497	3.016	2.092	0.782
Slope (°)	22	10.000	25.000	16.818	5.885
Cohesion (kPa)	22	0.000	10.000	3.864	4.063
Friction Angle (°)	22	10.000	30.000	20.455	8.439
Thickness (m)	22	1.000	4.000	2.818	1.368

3.3 Multiple linear regression

Before using the multiple linear regression model to predict the FoS, it is essential to calculate the correlation matrix, as shown in Figure 3.

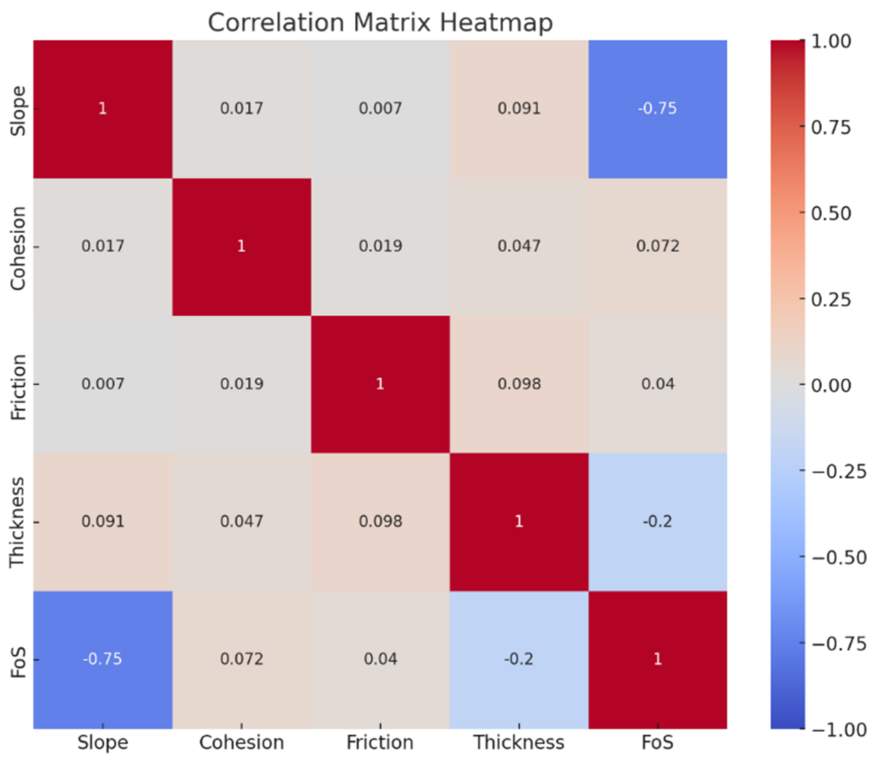

Figure 3 Pearson correlation matrix

The correlation matrix reveals several important relationships among the variables slope, cohesion, friction, thickness, and FoS. The strongest correlation observed is between slope and FoS, showing a strong negative correlation of -0.753, indicating that as the slope increases, the FoS significantly decreases. Thickness also shows a negative correlation with FoS (-0.200), though this relationship is weaker. Cohesion and friction have very weak positive correlations with FoS (0.072 and 0.040, respectively), suggesting minimal impact on the FoS. Additionally, the correlations between slope, cohesion, friction, and thickness are generally very weak, indicating that these variables do not strongly influence each other directly.

The results of the MLR model are depicted in Equation 1 which presents the generated formula for predicting the FoS. According to the model, the FoS decreases with an increase in slope angle and overburden soil thickness, while it increases with higher cohesion and friction angle of the overburden soil. These results align with the observed trends in the study, providing a quantitative tool for assessing the stability of slopes in brown coal mines.

$$FoS = 4.139 - 0.118 \times \alpha + 1.577 \times 10^{-2} \times c + 4.863 \times 10^{-3} \times \varphi - 7.175 \times 10^{-2} \times h \qquad (1)$$

where:

α = slope angle

c = cohesion of the overburden soil

ϕ = friction angle of the overburden soil

h = thickness of the overburden soil.

Figure 4 provides a comprehensive evaluation of the MLR model's performance in predicting the FoS for both training and testing datasets through various visualisations. Figure 4a shows the actual versus predicted values, illustrating a generally good fit with some deviation, especially for lower and higher FoS values. The histogram on Figure 4b compares the distribution of predicted and actual FoS values, indicating that the model tends to predict a wider range of FoS values compared to the actual values. The box plot at Figure 4c shows the distribution of predicted and actual FoS values for both training and testing datasets, highlighting the model's ability to capture the central tendency and variability. The violin plot on Figure 4d complements this by providing a detailed view of the data distribution and density, revealing a reasonable overlap between predicted and actual values, though some discrepancies are evident in the testing dataset.

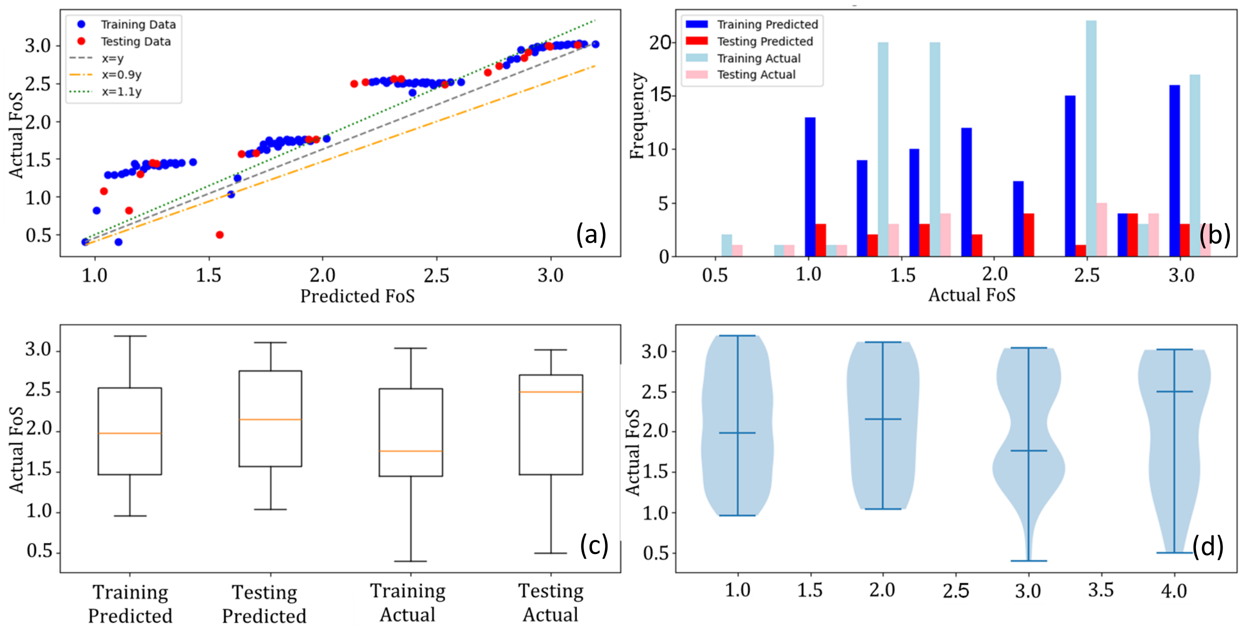

Figure 4 Comparison of multiple linear regression predicted versus actual Factor of Safety. (a) Line plot comparing actual and predicted values; (b) Histogram of predicted and actual values for training/testing data; (c) Box plot showing the range and medians of predicted versus actual values; (d) Violin plot visualising the distribution of predicted and actual values

The following metrics are used to show the accuracy of model predictions:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4}$$

where:

y_i = actual value of the i-th observation

$\hat{y}_i$ = predicted value of the i-th observation

n = number of observations

$\bar{y}$ = mean of the actual values.

The results of the MLR model for both training and testing datasets are presented in Table 6, indicating the model's performance through various metrics. The mean absolute error (MAE) for the training data is 0.132 and for the testing data is 0.181, showing the average absolute deviation of predictions from actual values. The root mean squared error (RMSE), which provides a measure of the magnitude of prediction errors, is 0.180 for training and 0.284 for testing. The coefficient of determination (R^2) is 0.832 for training and 0.762 for testing, signifying that the model explains 83.2% and 76.2% of the variance in the training and testing datasets, respectively.

Table 6 Results of multiple linear regression for training and testing databases

Heading	Training	Testing
MAE	0.132	0.181
RMSE	0.180	0.284
R^2	0.832	0.762

3.4 Genetic programming

The results from running different GP models have produced a complex and highly non-linear equation for predicting the FoS, as shown in Equation 5. The generated GP model equation, which incorporates the slope angle (α), cohesion of the overburden soil (c), friction angle of the overburden soil (φ), and thickness of the overburden soil (h), along with three constants, demonstrates the ability of GP to capture intricate relationships between these variables. The equation suggests that the interactions between these features are not straightforward and involve multiple multiplicative and subtractive terms, reflecting the complex nature of soil stability problems. This model, derived from normalised data, indicates that GP can effectively handle non-linearities and interactions in data, potentially leading to more accurate and robust predictions compared to traditional linear models. The detailed nature of this GP model highlights its strength in modelling sophisticated real-world phenomena where relationships between variables are intricate and multi-faceted.

$$(((R_2 \times R_3 - 2 \times \alpha + R_2) \times (R_2 \times R_3 - ((\alpha \times h - h) \times \alpha))) - (((h - c - \varphi \times \alpha) \times ((\alpha + h) \times R_3 \times R_1)) - R_3))) \tag{5}$$

where:

α	=	slope angle
c	=	cohesion of the overburden soil
φ	=	friction angle of the overburden soil
h	=	thickness of the overburden soil
R_1	=	0.135
R_2	=	0.587
R_3	=	0.636.

Figure 5a shows actual versus predicted FoS values for both training and testing data. The data points are scattered around the x=y line, which indicates perfect predictions. Most points cluster closely around this line, indicating that the model's predictions are generally accurate.

Figure 5b compares the distribution of actual and predicted FoS values. The training predicted values and training actual values show a similar distribution, suggesting the model has learned the training data well. However, the testing predicted values are more dispersed compared to the testing actual values, indicating that the model's performance on unseen data is less consistent. This discrepancy highlights the potential overfitting of the model to the training data.

Figure 5c displays the spread of FoS values for both predicted and actual data in training and testing datasets. The interquartile ranges (IQRs) for all four categories are similar, which suggests that the central tendencies and spreads are comparable. However, the testing data (both actual and predicted) show slightly larger whiskers, indicating higher variability in predictions and actual values in the testing set compared to the training dataset.

Figure 5d provides a detailed view of the data distribution and density. It shows that the predicted and actual values in the training data have a dense, consistent distribution. In contrast, the testing data exhibits a wider spread and less consistency, with predicted values showing multiple peaks. This suggests that while the model captures the overall trends, it struggles slightly with precise predictions in the testing phase.

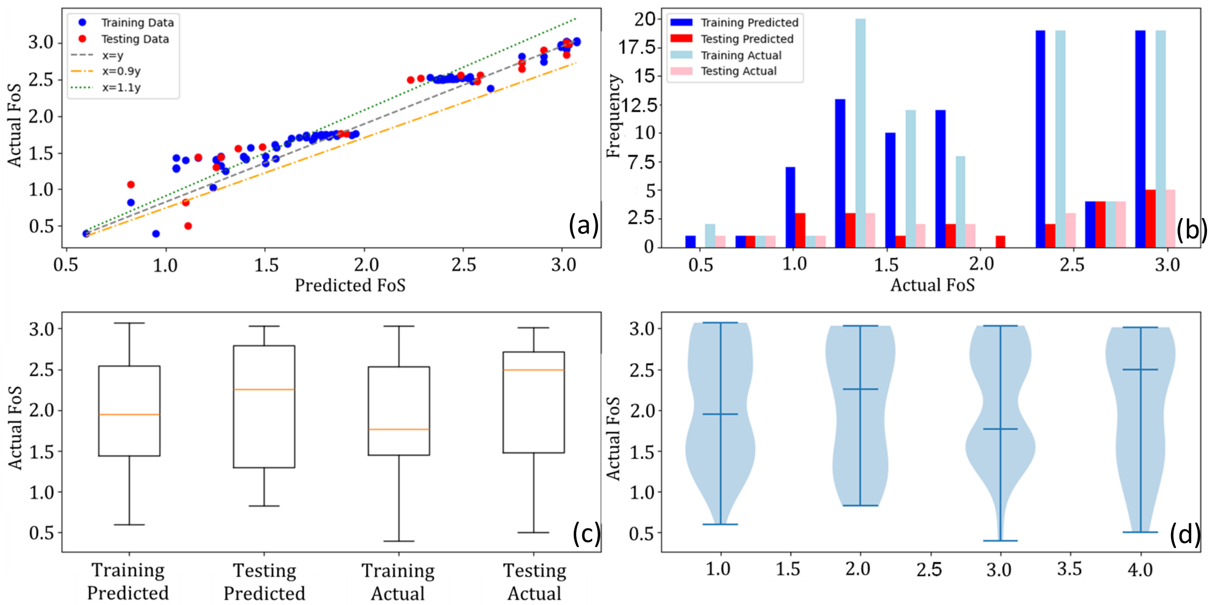

Figure 5 Comparison of genetic programming predicted versus actual Factor of Safety. (a) Line plot comparing actual and predicted values; (b) Histogram of predicted and actual values for training/testing data; (c) Box plot showing the range and medians of predicted versus actual values; (d) Violin plot visualising the distribution of predicted and actual values

The performance metrics for the GP model, presented in Table 7, demonstrate a notable difference in accuracy between the training and testing datasets. For the training database, the model achieves a MAE of 0.096 and RMSE of 0.133. These low values indicate high accuracy and minimal prediction errors within the training data. Similarly, the testing database shows small error metrics, with a MAE of 0.152 and RMSE of 0.204, suggesting reduced accuracy when predicting unseen data. Despite these higher errors, the model maintains a high R-squared (R^2) value of 0.929 in testing, only slightly lower than the 0.963 observed in training, indicating that the model still explains a significant portion of the variance in the data.

Table 7 Results of genetic programming model for training and testing databases

Metrics	Training database	Testing database
MAE	0.096	0.152
RMSE	0.133	0.204
R^2	0.963	0.929

4 Discussion

4.1 Comparison

Tables 8 and 9 present the performance metrics of two models used in the training and testing phases for predicting the FoS of the open pit mine. During the training phase, the GP model outperforms the MLR model across multiple metrics. In the testing phase, the GP model maintains its superiority over the linear model, enhances the predictive capability of the GP model.

Table 8 Results of multiple linear regression (MLR) and genetic programming (GP) models for training database

Metrics	MLR model	GP model
MAE	1.138	0.803
RMSE	1.315	0.956
R^2	0.877	0.935

Table 9 Results of multiple linear regression (MLR) and genetic programming (GP) models for testing database

Metrics	MLR model	GP model
MAE	1.458	0.639
RMSE	1.840	0.755
R^2	0.806	0.967

Figure 6 presents a comparison of the actual FoS values with the predicted values from two models: an MLR model and a GP model. The R-squared (R^2) values for both models indicate their accuracy, with the MLR model achieving an R^2 of 0.806 and the GP model achieving a higher R^2 of 0.967 for testing dataset. This suggests that the GP model may capture the underlying patterns in the data more effectively than the MLR model.

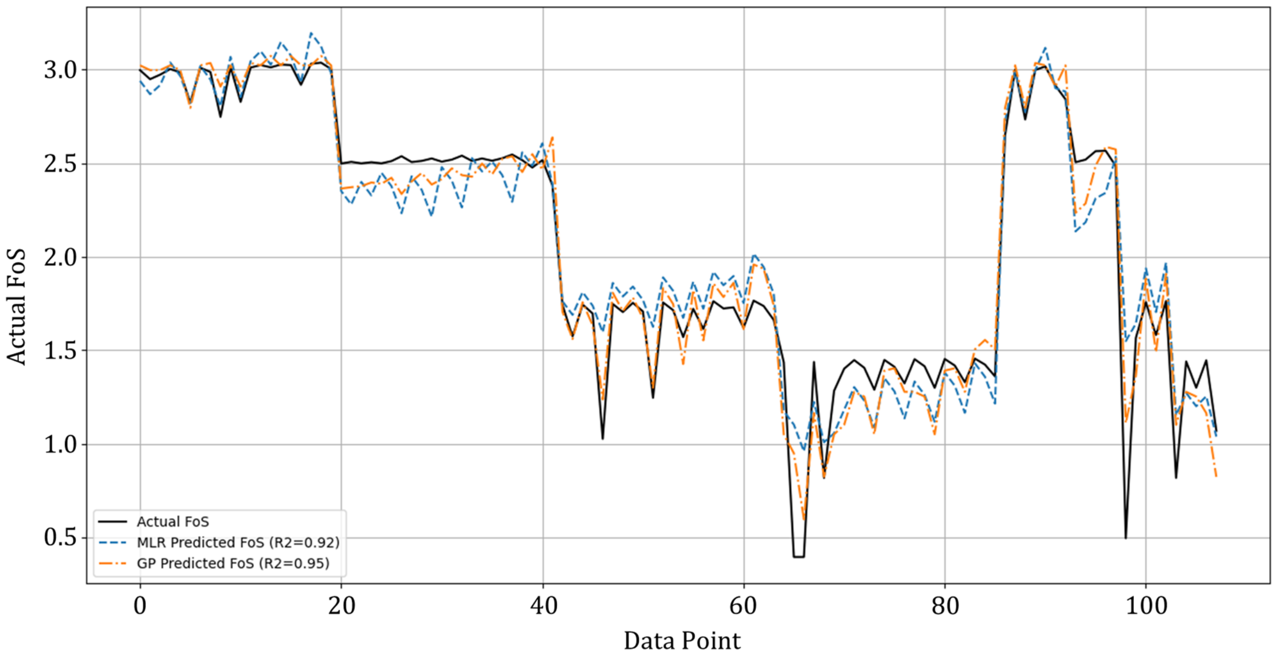

Figure 6 Results of genetic programming (GP) and multiple linear regression (MLR) models for both training and testing databases

4.2 Feature importance

According to Figure 7, the feature importance analysis for both the MLR and GP models reveals distinct differences in the contribution of each feature to the prediction of the FoS. In the MLR model (Figure 7a), the most influential feature is the slope angle (α), followed by the thickness of the overburden soil (h), the cohesion of the overburden soil (c), and the friction angle (φ). This indicates that the slope angle and thickness play a more significant role in determining FoS according to the MLR approach. Conversely, in the GP model (Figure 7b), the slope angle (α) also shows substantial importance, but the model exhibits a more complex interaction among the features, with the coefficients suggesting a varied influence of cohesion (c), friction angle (φ), and thickness (h) due to the non-linear nature of the genetic programming equation. This complexity in the GP model underscores its potential to capture intricate relationships between variables, potentially providing more accurate predictions by considering the combined effects of multiple factors in a non-linear manner. The contrast between the two models highlights the strengths of MLR in simplicity and interpretability, while the GP model excels in capturing more nuanced relationships within the data.

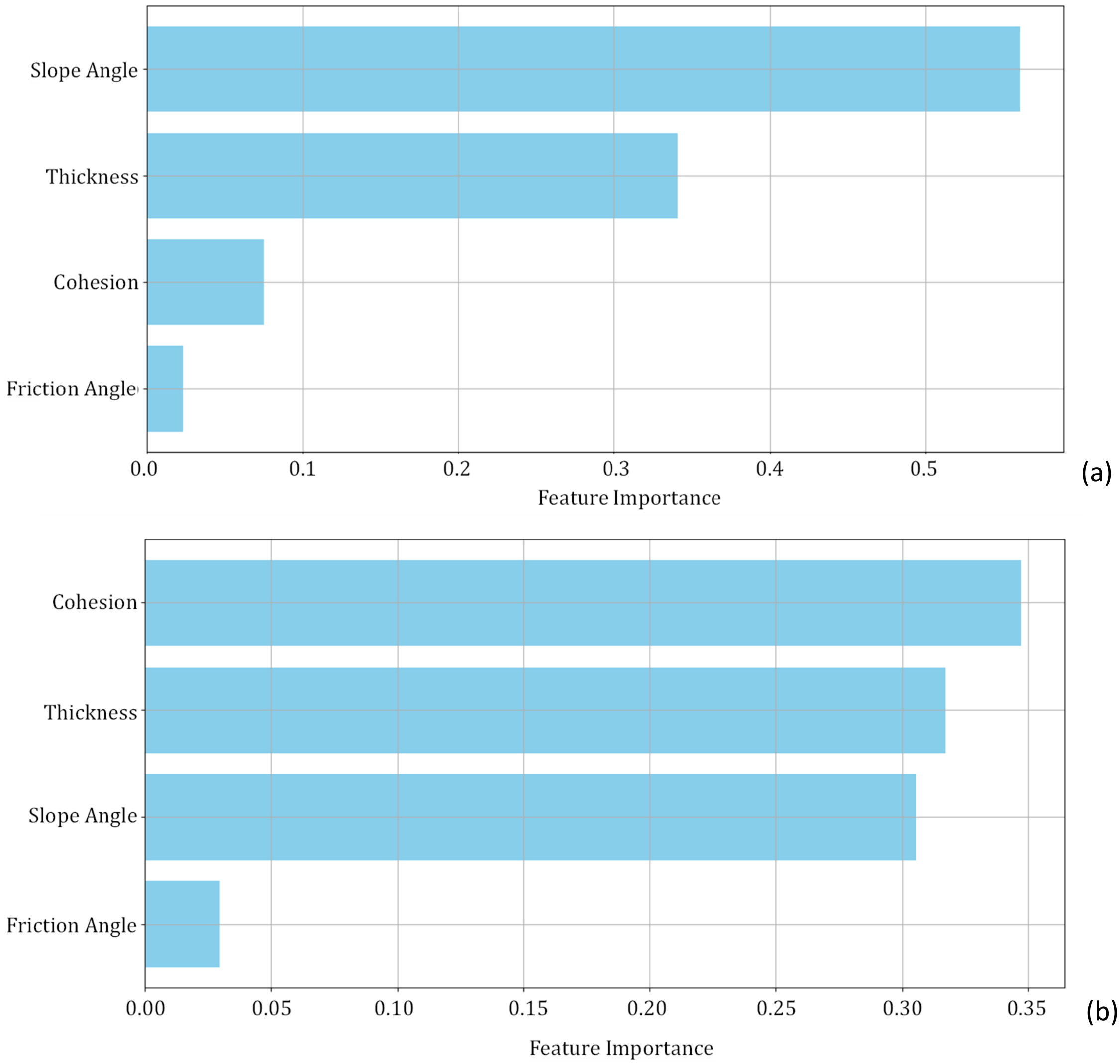

Figure 7 Results of feature importance for (a) multiple linear regression and (b) genetic programming

5 Conclusion

This study successfully demonstrates the application of both numerical and AI techniques in predicting the stability of the Victoria Open Pit Mine slopes in the Latrobe Valley. By leveraging MLR and GP models, the research offers valuable insights into the factors influencing slope stability under the specific conditions tested in this study. It is important to note, however, that the generalisation of these findings, particularly regarding the relationship between slope angle and stability, should be approached with caution. Other critical factors, such as geological structures, groundwater levels, and structural feature orientation, can significantly alter stability outcomes, and these are not fully addressed within this study.

While the GP model demonstrated superior performance with higher R-squared values for both training (0.935) and testing (0.967) datasets compared to the MLR model (0.877 and 0.806, respectively), it is essential to acknowledge the limitations of the input data. This study serves as a proof-of-concept for applying AI to slope stability, but further development and refinement of the models are needed to incorporate a broader range of geotechnical factors. The feature importance analysis underscored the dominant role of slope angle, but interactions between other variables such as cohesion, friction angle, and overburden thickness also played a role in stability predictions.

Readers should interpret these findings within the specific scope of this study and recognise the need for further research to address gaps in knowledge, particularly regarding the integration of more comprehensive geotechnical data. The results presented here highlight the potential of AI-based approaches, particularly GP, to model complex geotechnical phenomena and enhance predictive capabilities. However, the accuracy and applicability of these models can be further improved with more detailed input data, ensuring their reliability in the design and management of safe and efficient mining operations.

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