Natural Hazards
https://doi.org/10.1007/s11069-024-06819-3

ORIGINAL PAPER

Development of a framework for the prediction of slope stability using machine learning paradigms

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Received: 15 March 2024 / Accepted: 12 July 2024

Abstract
Accurate slope stability prediction is of utmost importance to reduce disastrous effects of slope failures and landslides. However, conventional methods of slope stability analysis are complex and challenging, and more importantly, use of these methods in a wide-area slope stability assessment requires a large number of soil property and field investigation data. These complexities and challenges often demand some simplified statistical slope stability analysis models such as by using machine learning (ML) techniques. So, in this research, we develop slope stability prediction models using multiple linear regression (MLR) and artificial neural network (ANN) and classify the slopes as safe or unsafe using random forest (RF) and support vector machine (SVM) methods. For this purpose, a dataset of 4,208 slope cases was created using limit equilibrium-based Slide software. The effectiveness of each model was then evaluated using statistical metrics and validated through roadside slope cases in Nepal, India, Canada, and the UK. In this study, Spencer's method-based ANN model was found to have demonstrated the highest reliability. The findings of this work may contribute to simplified and better decision-making process in slope stability assessment, slope safety enhancement, and sustainability improvement in engineering projects involving soil slopes.

Keywords Slope stability · Machine learning · Stability prediction models · FOS · ANN · MLR

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Published online: 25 July 2024

1 Introduction

Slope geometry, properties of the slope soil and rock masses, slope hydrological environment, existing reinforcing elements, applied loads, and seismicity of the area are the key elements that govern the stability of a soil or rock slope (Zou et al. 2021; Nasseri et al. 2022). Slope failure events are often disastrous and may lead to fatal loss, destruction of properties and infrastructures, and great economic impact (Sim et al. 2022; KC et al. 2024). Rapid growth in development and construction activities especially in developing countries with mountainous terrains demands some accurate but simple methods to predict the stability of slopes (He et al. 2003).

The traditional slope stability analysis methods such as Bishop (1955), remains one of the best methods for soil stability analysis due to its balance of computational simplicity and accuracy. It effectively estimates the factor of safety for circular slip surfaces by simplifying complex limited equilibrium equation, making it widely acceptable and reliable in geotechnical applications. While historically significant, classical slope stability methods are time-consuming, labour-intensive for wide-area assessment, requiring extensive soil property data and field investigations (Choobbasti et al. 2009). Owing to these drawbacks, addressing the landslide and slope stability issues more effectively requires expertise in several fields, such as geology, hydrology, seismology, geotechnical exploration, and geotechnical engineering, along with the proficiency in computerized analytical methods and feasible solutions (Aryal and Acharya 2022; Choobbasti et al. 2009). So, developing countries with young geology, steep terrains, and intense rainfall in a short period, such as India, the Philippines, Indonesia, Nepal, etc. entail affordable and straightforward models to assess the stability of soil slopes.

Machine Learning (ML) have the potential to overcome the limits of conventional slope stability analysis techniques. One key advantage is their ability to incorporate numerous influencing elements, capture complex interactions within the data, and efficiently handle large and heterogeneous datasets (Aminpour et al. 2022; Liu et al. 2021; Qi and Tang 2018). Furthermore, ML models offer the potential for automation and scalability, allowing for rapid analysis of slope stability across large spatial scales and diverse geological settings (Bansal and Sarkar 2024). Favourable results have been observed in applying ML for slope stability analysis providing robust, simplified and accurate predictions, as documented by Das et al. (2011) and Koopialipoor et al. (2019). Melchiorre et al. (2008), Pradhan et al. (2010), and Wang et al. (2006) employed ANNs to evaluate and predict the deformation of landslides in the regional areas of Italy, Malaysia, and Japan, respectively. Lin et al. (2021) proposed a model using 11 different ML algorithms and a total dataset of 396 slope cases to systematically compare the effectiveness of each algorithm. They found that support vector machine (SVM), gradient boosting machine (GBM), and bragging were the most suitable algorithms for slope stability prediction. Chakraborty and Goswami (2017) utilized 200 artificial slopes to develop prediction models based on MLR and ANN, demonstrating their effectiveness with high correlation values and low error metrics. Bui et al. (2019) found that the multi-layer perceptron (MLP) outperformed other machine learning models in predicting slope stability, based on a dataset of 630 stages derived from simple layer cohesive slope. Ray et al. (2020) developed ANN_1 and ANN_2 models using 400 residual soil slopes to estimate the FOS in the Siwalik slopes of the Himalayas. Karir et al. (2022) use various machine learning models to predict the factor of safety for natural residual soil slopes and man-made mine dump slopes and found tree-based algorithms, particularly extreme gradient boost, to be superior in performance compared to linear models. Demir and Sahin (2023) evaluated five machine learning algorithms for predicting slope stability and discovered winsorizing data improves model performance, with random forest (RF) performing best. Various machine learning algorithms were explored by Kurnaz et al. (2024) for slope stability analysis and found that the weighted ensemble learning algorithm in the AutoGluon package yields the most accurate results.

Despite a few studies on use of ML models to analyse slope stability using smaller datasets, a comprehensive evaluation utilizing state-of-the-art ML techniques and extensive datasets has yet to be conducted. For ML models to be successful during the learning, testing, and validation procedures, trustworthy and sizable datasets must be available (Dashbold et al. 2023; Pyakurel et al. 2023; Ye et al. 2022). The main contribution of this study lies in the development and comprehensive evaluation of a framework for forecasting the factor of safety (FOS) of slopes using state-of-the- art ML paradigms, specifically MLR, ANN, RF, and SVM, on significantly larger dataset than previously utilized. By generating a dataset of 4208 slope cases using limit equilibrium-based Slide software for sensitivity analysis, regression, and classification model development, this study provides a robust method for slope stability prediction. Accurate estimates of the FOS constitute a significant criterion for assessing slope stability, allowing geologists and geotechnical engineers to make informed decisions throughout a project's planning and design phases. This can be helpful in decision-making processes and in improving the safety and sustainability of engineering projects in slope-prone areas.

2 Materials and methods

2.1 Data and slope models

The stability of slopes is governed by geometric attributes of the slope (i.e., inclination and height) and material properties (i.e., cohesion, angle of internal friction, pore water pressure, and unit weight of soil). These parameters were used to estimate the FOS of the slope. When the FOS >1, the slope was classified as stable, and when the FOS ≤ 1, the slope was classified as unstable. The purpose of this study is to explore the performance of various artificial intelligence-based algorithms in evaluating the stability of slopes, both regression and classification models were used to predict the FOS and slope classification as model outputs. The performance of each model was evaluated by accuracy score and coefficient of determination.

To accurately predict the FOS, the dataset must be sufficient in number to represent the phenomenon being predicted effectively. The model must train with known datasets covering a wide range of inputs to predict the intricate relationship between dependent and independent variables. The homogenous slope with the variation of these input parameters was modelled to obtain a FOS for the five different limit equilibrium methods, i.e., Bishop (1955), Fellenius (1936), Janbu (1955), Morgenstern and Price (1965), and Spencer (1967).

Limit equilibrium-based Slide software was used to evaluate the FOS of the slope from six different parameters, namely, slope angle (θ), height (H), cohesion (c), angle of internal friction (ϕ), pore pressure coefficient (r_u), and unit weight of soil material (γ). A total of

4,208 parametric scenarios were gathered to create the datasets based on different ranges of the parameters of the slopes as shown in Table 1. The obtained FOS for different parametric features was used to prepare the comprehensive database for further study using ML algorithms. All input and outcome variables utilized in this study are also statistically summarized in Table 1.

The parameter ranges for our landslide prediction model were determined based on a comprehensive review of the literature. Previous studies (Abbas 2014; Chen et al. 2021) have established the importance of parameters such as slope angle, slope height, soil type, unit weight and cohesion in slope stability. The height of the slope was chosen within the range of 10 m to 35 m (Table 1) to provide sufficient stability for small-scale slope instability occurring alongside roads. Large landslides that can cause more extensive damage can be analysed on an individual basis. The pore pressure coefficient ranges from 0 to 1, where 0 indicates a completely dry condition, and 1 represents a saturated condition. Slope inclinations were adopted to range from 20º to 45º, as in the studies done by Juang et al. (1992), Kasa (1992), and Ray et al. (2020) in which the landslides appearing in the area occurred at locations with slopes exceeding 20º. For the soil modelling, the cohesion was adopted to vary from 0 kPa to 20 kPa, as adopted by Paudyal et al. (2023). In terms of friction angle (15° – 35°) and unit weight (15–25 kN/m^3), the ranges of value considered in the study covers a wide range of soils.

Landslides are complex phenomena involving physical interplay of several parameters. For example, increased pore pressure (higher r_u) reduces effective stress in the soil, decreasing friction and cohesion, and thus lowering slope stability (Lehtonen 2015; Thakur et al. 2021). The exact relationship between pore pressure and friction or cohesion is influenced by factors like soil type, pore structure, and groundwater, complicating precise determination (Acharya et al. 2023; Subedi et al. 2021). However, this paper does not detail the role of each parameter in slope stability or the interactions between these parameters.

The total number of datasets were divided into training and testing subsets, each of which was 80% and 20% of the total datasets, respectively. In total, the training and testing subsets were 3,366 and 842, respectively. The slopes with FOS were classified into two classes, safe slope, and unsafe slope, which are assigned numerical encoding as 1 and 0, respectively. Slope cases with FOS value greater than two and less than 0.2 are trimmed off so that the ML prediction model can obtain enough data for boundary classification. The values below 0.2 indicate extreme instability, often outliers, while values above 2 represent very stable conditions with negligible failure risk. Excluding these extremes focuses the model on rel-

Table 1 Statistics of variables used in the analysis

Property	Variables						
	Slope Height, H (m)	Slope Inclination, θ (°)	Cohesion, c (kPa)	Friction Angle, ϕ (°)	Unit weight, γ (kN/m^3)	Pore pressure coefficient, r_u	Factor of safety (FOS)
Category	Input	Input	Input	Input	Input	Input	Output
Count	4,208	4,208	4,208	4,208	4,208	4,208	4,208
Mean	22.23	35.43	10.06	25	20	0.49	0.67
Min	10	20	0	15	15	0	0.2
Max	35	45	20	35	25	1	1.95
Std. Deviation	9.27	7.27	2.91	3.01	1.5	0.12	0.23

evant stability ranges, improving the model training and enhancing prediction accuracy. The training dataset for our landslide prediction model has an average Factor of Safety (FOS) of 0.67. This average value was chosen to avoid bias towards either stable or unstable slopes, even though an FOS of 0.67 indicates instability. Different FOS assumptions could lead to overprediction (with a very low FOS) or underprediction (with a very high FOS) of landslide occurrences. The FOS of 0.67 reflects the dataset characteristics, as we include data for landslide events where the FOS is less than 1. By adhering to these dataset characteristics, we enhance the model's robustness and applicability in real-world scenarios where the distribution of slope stability may vary from our training set. On the other hand, determining the best architecture of ML was also challenging in developing the best-performing model. The model development steps are described with the help of a flowchart, as mentioned in Fig. 1.

2.2 Machine learning models

Machine learning (ML) models attempt to represent slopes' complex linkages and nonlinear behaviour by combining various geometric and soil properties. The factor of safety (FOS) of slopes, which stands for the margin of safety against failure, and input variables such as geometry, soil parameters, and pore water pressure can be captured reasonably by ML algorithms.

Table 2 shows some of the studies conducted in the past to study slope stability using different ML methods. In this study, two different sets of supervised machine-learning algorithms are used. Based on input variables, including c, ϕ, r_u, and γ, supervised regression models were used to anticipate the FOS. Meanwhile, supervised classification models were utilized to categorize slopes as either safe or unsafe.

2.2.1 Artificial neural network (ANN)

Artificial neural network (ANN) is a computational model that attempts to duplicate the brain's core function by functioning similarly to the brain's neurons. It is composed of

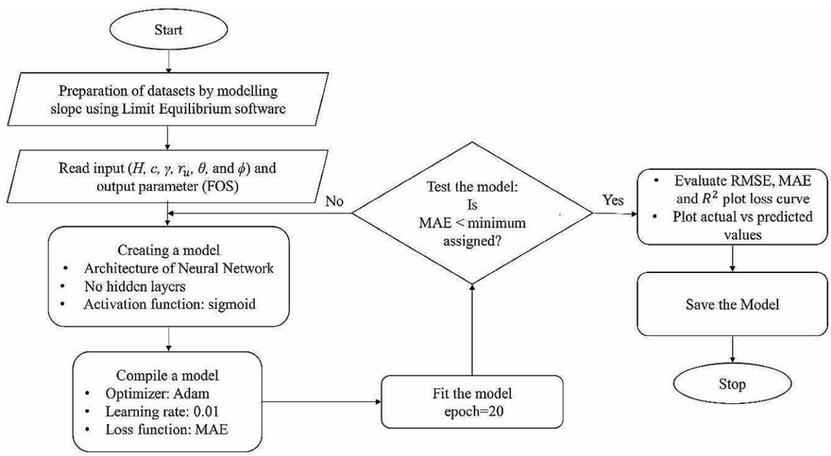

Fig. 1 Flow chart for development of machine learning model

Table 2 Summary of previous studises on ML-based slope stability prediction

Source	Parameters	Data size	Model Used
Samui (2008)	c, H, θ, γ, ϕ, r_u	46	SVM
Gelisli et al. (2015)	c, H, θ, γ, ϕ, WT	100	ANN
Chakraborty and Goswami (2017)	c, H, γ, ϕ, β, r_u	200	MLR and ANN
Qi and Tang (2018)	c, H, θ, γ, ϕ, r_u,	148	RF, GBM, SVM, ANN, LR, DT
Bui et al. (2019)	c, θ, b/B, w	630	GPR, MLR, MLP, SLR, SVM
Ray et al. (2020)	C_s, $C_{j,}C_r$, H, ϕ_s, ϕ_r, $\phi_{j,}E_r$, E_s, α, D	400	ANN (both ANN1 and ANN2)
Lin et al. (2021)	c, H, γ, β, ϕ, r_u,	396	LR, BR, ENR, KNN, SVM, DT, RF, Ada boost, GBM, Bagging, Extra trees
Bharati et al. (2022)	H, θ, h'	216	ANN and MLR

where θ: Slope angle, H: Slope height, c: Cohesion, ϕ: Friction angle, E_s: Young's modulus, h: Soil depth, b/B: Slope setback distance, w: Surcharge, WT: Height of water table, h': Collar height, C_s: Shear strength of residual soil, ϕ_s: friction angle of residual soil mass, E_r: Young's Modulus of Weathered rock mass, C_r: Cohesion of weathered rock mass, ϕ_r: angle of internal friction of Weathered rock mass, C_j: cohesion of soil rock joint interface and ϕ_j: angle of internal friction of rock joint interface, α: average slope angle (α), D: residual soil depth, GBM: Gradient boosting Machine, LR: Logistic Regression, DT: Decision Tree, BR: Bayesian Ridge, ENR: Elastic net regression, KNN: K nearest neighbours, Ada boost: Adaptive boosting Machine, GPR: Gaussian Processes Regression, MLP: Multi-Layer Perceptron, SLR: Simple Linear Regression

many interconnection processing units (neurons), that works together to solve specific problems. Haykin (1999) described ANNs as machines designed to model the process of human mind during particular task. When the connections within the underlying data are hidden or obscure, ANNs prove to be a powerful modelling tool.

ANN generally contains three primary layers: the input, hidden, and output (Cho 2009). Multilayer neural networks are more reliable than single-layer neural networks for solving nonlinearly separable issues such as slope stability analysis because of their ability to combine linear transformations and sigmoidal functions (Chakraborty and Goswami 2017; Zare et al. 2013). Multilayer perception (MLP) is a simple type of ANN can incorporate the non-linear relationship between sets of input features and target labels.

However, there is not much benefit to using several hidden layers. Yilmaz (2010) observed that if there are enough nodes in a single hidden layer of an MLP, it can effectively approximate any function with reasonable accuracy. When the optimal quantity of nodes in a single hidden layer is substantial, employing two hidden layers can be reasonable. Once the network has learned, it can apply its acquired understanding to anticipate the actual output with a respectable degree of accuracy.

The optimum performing neural network can be obtained after experimenting with different hidden layers, activation functions, optimizers, and corresponding neurons within each layer. On both the training and testing datasets, a number of trials were performed to determine the minimum mean absolute error (MAE) and the maximum coefficient of determination (R^2). The hidden layer with ten neurons was chosen as a best model, preventing further complexity of architectural design. The best-performing model employs the Adam optimizer with a learning rate of 0.01 and sigmoid function as the activation function. The quantity of input and output variables determines the maximum number of neurons possible on the input and output layers. Specifically, the input layer comprises six neurons, while the output layer comprises only one neuron. Architecture of the ideal model for the ANN regression approach is shown in Fig. 2.

2.2.2 Multiple linear regression (MLR)

Multiple linear regression (MLR) is a vital regression algorithm that models the linear relationship between several independent variable and a single dependent continuous variable. This method is frequently employed in the prediction of landslides and slope failures (Pradhan et al. 2010). By using more than one predictor variable to obtain a criterion value, MLR is an improvement over simple linear regression. The general MLR is given by Eq. (1):

$$Y = a + b_1 \times x_1 + b_2 \times x_2 + b_3 \times x_n + \ldots + b_n \times x_n + \varepsilon \tag{1}$$

where Y is a dependent variable, $x_{1,}$ x_2, x_3, …, x_n are independent variables, $b_{1,}$ b_2, b_3, …, b_n are regression coefficients, a is constant, and Ɛ is an error.

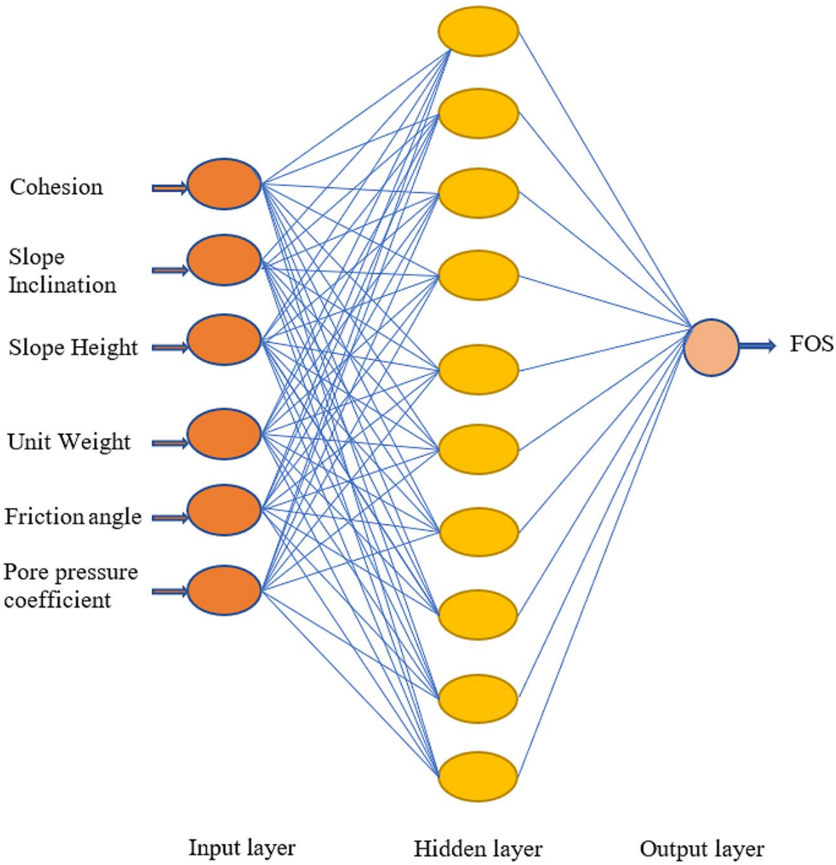

Fig. 2 Neural network architecture for FOS prediction

2.2.3 Random forest (RF)

Random forest (RF) is a popular machine learning algorithm for classification and regression that operates by many decision trees at training time. Instead of depending on a single decision tree, the RF estimates from each tree based on most predictions and predicts the final output. It utilizes combined decision trees from weak learner decision trees by employing resampled datasets, substations, and randomly changed predictors (Breiman 2001). A higher number of trees in the forest increases accuracy and reduces the issue of overfitting. Breiman (2001) statistical theory is the foundation of the RF algorithm, which is combination classification intelligence. It can mine data effectively and anticipate outcomes with great precision (Huang et al. 2022; Lin et al. 2018).

An RF eliminates the drawbacks of a decision tree algorithm. It decreases the overfitting of datasets and increases precision. The likelihood of overfitting can be decreased by the number of random trees because each tree acts as a totally distinct random circumstance (Wongvibulsin et al. 2020).

2.2.4 Support vector machine (SVM)

Support Vector Machine (SVM) is one of the widely used supervised learning algorithms employed for classification and regression problems. The SVM identifies a hyperplane within an N-dimensional space (N is the number of features) that effectively separates the data points into distinct classes. Due to their remarkable performance in handling high-dimensional and non-separable datasets, SVMs have shown to be a dependable solution for many classification problems (Kavzoglu and Colkesen 2009).

Many possible hyperplanes could be chosen to distinguish two data points. Our aim is finding a plane with maximum margin, i.e., the greatest distance between data points of two classes. By maximizing the margin distance, the classification process is strengthened and confidence in classifying future data can be enhanced. The system output is generated by grouping and classifying the relationships among these predictors (Gleason and Im 2012). The fundamental principle of SVM is based on the transition from nonlinear to future linear spaces (Cherkassky and Mulier 2007).

Based on statistical learning theory, SVM enhances the generalization capacity of a learning machine by reducing structural risk, experience risk, and confidence range, enabling the model to be more accurate even when working with fewer samples.

3 Results

3.1 Sensitivity analysis

The sensitivity of the material properties to the FOS for a slope with a height of 35 m and an angle of slope inclination of 45° is presented in Fig. 3. In the figure, the x-axis represents the FOS, while the y-axis represents the percentage of range (%), which refers to the normalized variation of a material property from its minimum to maximum value, ranging from 0 to 100%. Sensitivity analysis helps to understand the influence of input parameters on the stability of the slope.

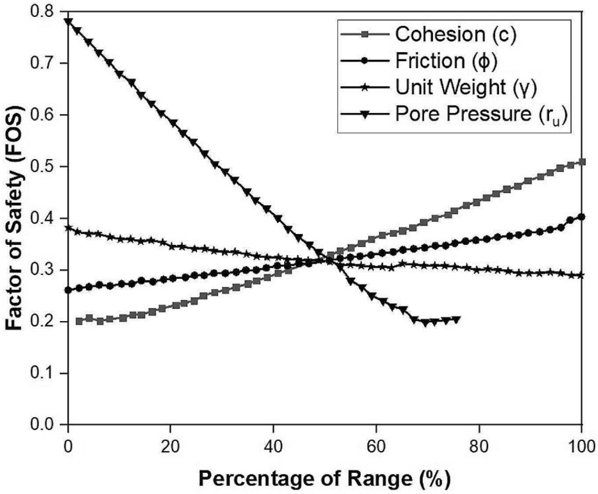

Fig. 3 Sensitivity plot of the material for cohesion, angle of friction, unit weight, and pore pressure coefficient

Table 3 Combination of slope angle (θ) and slope height (H) used for sensitivity analysis

Slope height, H (m)	Slope angle, θ (°)
10	25, 30, 35, 40
15	20, 30, 40, 45
25	25, 30, 35, 40, 45
30	30, 35, 40, 45
35	30, 35, 40, 45

Sensitivity analysis was performed on combination of slope inclination and height, as shown in Table 3. For the given slope angle (θ) and slope height (H), the result of sensitivity analysis was further used in the dataset development of this work.

3.2 Regression models

The Pearson correlation coefficient (r) between two variables, X and Y, can be estimated as Eq. (2). The entire dataset was examined to detect correlated features and to remove the redundant columns from the predicted models. According to the heatmap, there were no significant positive or negative correlations among the input variables. There were no redundant variables among the data features, making these input parameters suitable for use as features in prediction models.

$$\mathrm{r} = \frac{\sum\left(X_i - \bar{X}\right)\left(Y_i - \bar{Y}\right)}{\sqrt{\sum\left(X_i - \bar{X}\right)^2 \sum\left(Y_i - \bar{Y}\right)^2}} \tag{2}$$

A FOS value for the training dataset is obtained using Bishop, Fellenius, Janbu, Morgenstern and Price, and Spencer methods to create the datasets. For both MLR and ANN, five

Table 4 Summary output of MLR analysis for different slope stability methods

Study Parameters	Morgenstern and Price (1965)	Bishop (1955)	Janbu (1955)	Fellenius (1936)	Spencer (1967)
Multiple R	0.970	0.974	0.972	0.962	0.970
R^2	0.942	0.948	0.946	0.925	0.942
Adjusted R^2	0.942	0.948	0.945	0.925	0.942
Standard error	0.066	0.064	0.062	0.065	0.065
Number of observations	4208	4208	4208	4208	4208
Intercept	1.858	1.924	1.838	1.530	1.851
H	-0.014	-0.014	-0.013	-0.013	-0.014
c	0.026	0.026	0.023	0.024	0.026
ϕ	0.014	0.013	0.012	0.019	0.014
θ	-0.022	-0.023	-0.022	-0.017	-0.022
r_u	-1.072	-1.151	-1.120	-0.885	-1.070
γ	-0.013	-0.013	-0.012	-0.012	-0.013

Table 5 Prediction equations based on the MLR model for estimation of FOS for given input soil parameters

Method	Equation
Morgenstern and Price (1965)	$FOS = 1.858 - 0.014 \times H + 0.026 \times c + 0.014 \times \phi - 0.022 \times \theta - 0.022 \times \theta - 1.072 \times r_u - 0.013 \times \gamma$
Bishop (1955)	$FOS = 1.924 - 0.014 \times H + 0.026 \times c + 0.013 \times \phi - 0.023 \times \theta - 1.151 \times r_u - 0.013 \times \gamma$
Janbu (1955)	$FOS = 1.838 - 0.013 \times H + 0.023 \times c + 0.012 \times \phi - 0.022 \times \theta - 1.12 \times r_u - 0.012 \times \gamma$
Fellenius (1936)	$FOS = 1.530 - 0.013 \times H + 0.024 \times c + 0.019 \times \phi - 0.017 \times \theta - 0.885 \times r_u - 0.013 \times \gamma$
Spencer (1967)	$FOS = 1.851 - 0.014 \times H + 0.026 \times c + 0.014 \times \phi - 0.022 \times \theta - 1.072 \times r_u - 0.013 \times \gamma$

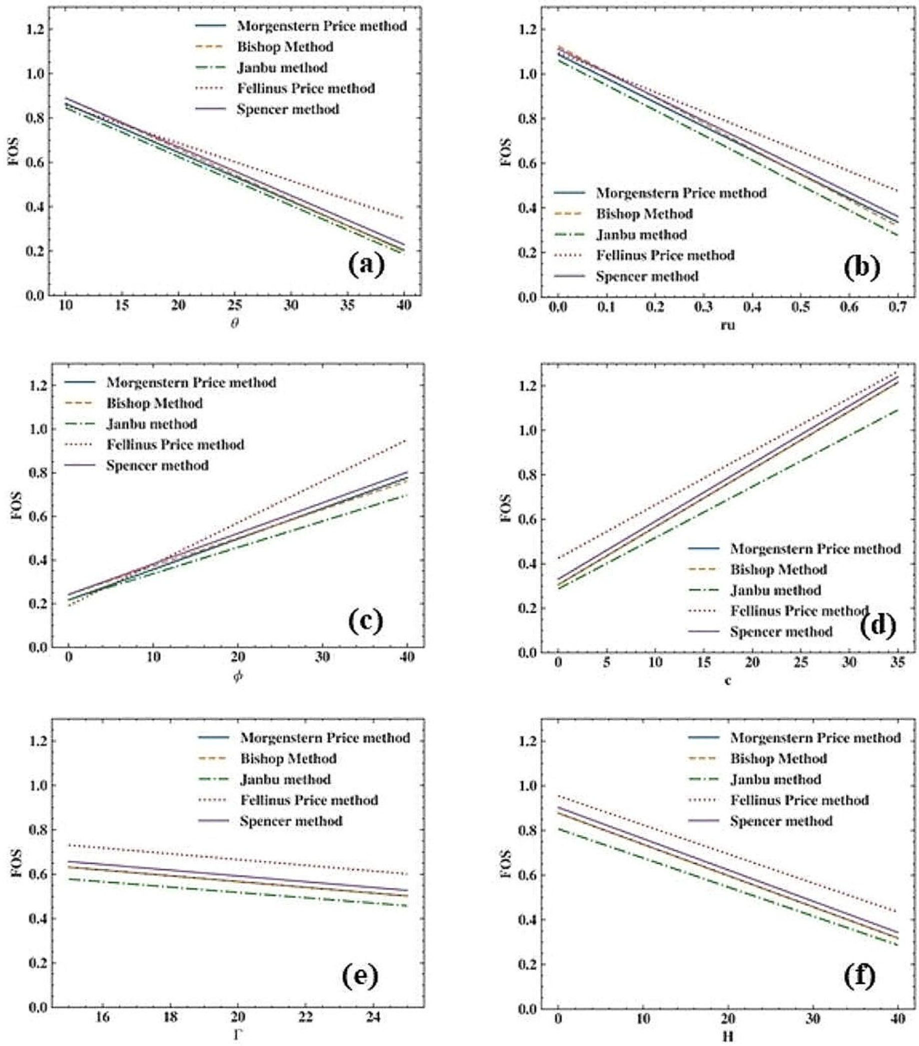

Fig. 4 Variation in FOS with input features as predicted from MLR: (**a**) slope (θ), (**b**) pore pressure coefficient (r_u), (**c**) angle of internal friction (ϕ), (**d**) cohesion (c), (**e**) unit weight (γ), and (**f**) height (H)

separate regression models were generated. The MLR model gives a predictive equation for the determining FOS, whereas the ANN model provides weights and biases for neural network, which were used for forecasting FOS based on input parameters.

3.2.1 Multiple linear regression (MLR)

A summary of the MLR analysis and corresponding statistics is given in Table 4. Table 5 demonstrates the prediction equation for each approach based on the MLR model.

The result of each input parameter with FOS predicted using MLR is shown in Fig. 4. Each value of the input features was taken one at a time, while other features remained at

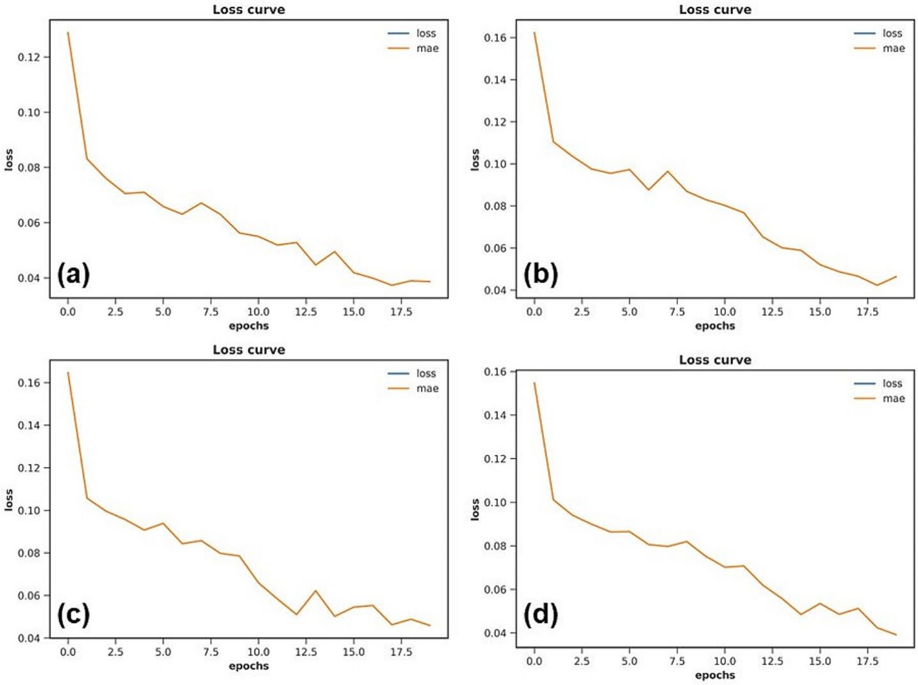

Fig. 5 Curve showing the loss between target and predicted outputs as a function of epochs for (**a**) Fellenius, (**b**) Bishop, (**c**) Janbu, and (**d**) Spencer methods

Table 6 Comparison of prediction performance in the ANN model for different stability analysis methods

ANN model for different methods	Value of R^2	
	Training data	Testing data
Fellenius (1936)	0.96	0.97
Bishop (1955)	0.95	0.96
Janbu (1955)	0.96	0.96
Spencer (1967)	0.97	0.97
Morgenstern and Price (1965)	0.95	0.95

the mean value of the overall instances in the datasets, as presented in Table 1. The FOS value increases with increasing values of ϕ and c and decreases with increasing values of θ, r_u, γ, and H.

3.2.2 Artificial neural network model (ANN)

The loss curve with epochs for each method is presented in Fig. 5. Among the models, the Spencer method shows superior performance in both the training ($R^2=0.97$) and testing ($R^2=0.97$) datasets, as shown in Table 6. Hence, the predicted result from the Spencer method aligns with the target output. The performance of all the other models is also excellent, as the value of R^2 is very high, close to 1.

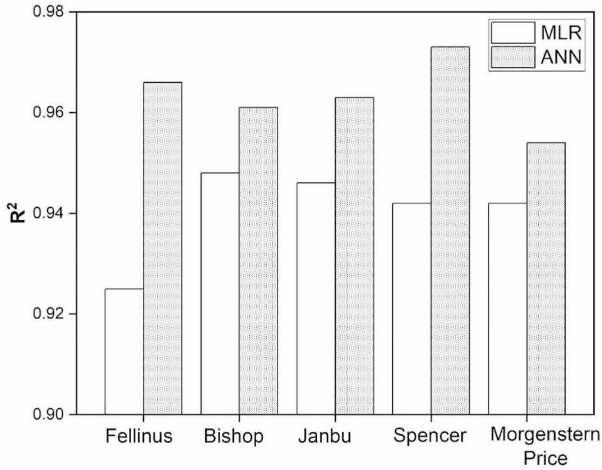

Fig. 6 Comparison of the performance of the MLR and ANN models for five limits equilibrium methods for soil stability

All artificial neural network regression models for the Bishop, Fellenius, Janbu, Morgenstern and Price, and Spencer methods are a good fit for the prediction of the FOS for given input features θ, H, r_u, c, ϕ, and γ, with the coefficient of determination of each being greater than 0.95.

3.2.3 Comparison of MLR and ANN regression models

Figure 6 demonstrates the bar plot comparing the R^2 for the ANN and MLR. The forecast performance of the ANN model surpasses that of the MLR models for each method. The prediction performance of the ANN model can be improved, increasing the model's complexity. MLR is a linear predictor, whereas ANN is a nonlinear predictor of the relationship between features and labels. The relation between FOS and input features is nonlinear and complex, and ANN models can be used for better prediction over MLR.

3.3 Classification models

In the model, FOS has two values, 0 and 1, which determine slope stability. A value of 0 in the model indicates that the unstable slope has a FOS less than 1, while a value of 1 indicates that the stable slope has a FOS greater than 1. The results of the classification models are discussed in terms of their classification accuracy, confusion matrix, classification report, and ROC curve. A comparison of each model in terms of prediction performance is also made.

3.3.1 Support vector machine (SVM)

The accuracy of the support vector classification model on the training dataset is 0.993. This means that the SVM model is good enough to classify slope stability problems. The SVM model for training data correctly predicts 99 out of 100 cases.

Table 7 Evaluation criteria estimate for support vector machine

Attribute	Precision	Recall	F1 score	Support
1	0.95	0.93	0.94	61
0	0.99	1	1	781
Accuracy			0.99	842
Macro average	0.97	0.97	0.97	842
Weighted average	0.99	0.99	0.99	842

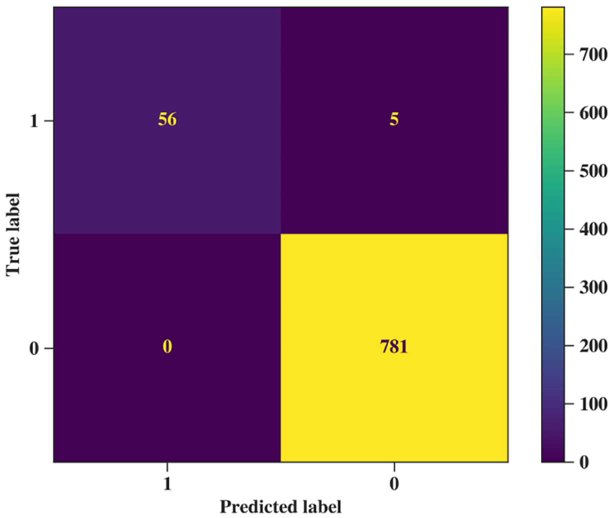

Fig. 7 Confusion matrix for support vector machine (SVM)

The accuracy of the training dataset using the SVM model is 0.992. This means that the support vector machine model is good enough to classify slope stability problems. The SVM model for unseen testing data correctly predicts 99 out of 100 cases.

Table 7 shows the details of the classification report for the support vector machine learning classification model. Out of all datasets that the model predicted as unstable, only 99% are unstable. Out of all datasets that the model predicted as stable, 95% were stable. Out of all stable datasets, the model correctly predicted 93% of those, and out of all unstable datasets, the model correctly predicted 100%.

Our model prediction is better because the F1 score for unstable slopes (1) and stable slopes (0.94) is closer to one. However, the F1 score for a stable slope is lower than that for an unstable slope. The SVM model predicts an unstable slope more correctly than a stable slope.

Figure 7 shows the confusion matrix classified from the support vector machine model. Out of 842 total test datasets.

- Fifty-six data points were classified as true positives, implying that the classification model correctly identifies stable slopes as stable.
- Five data points are false negatives, implying that the classification model incorrectly labelled stable slopes as unstable.
- Zero data are false positive as the classification model falsely labels unstable slopes as stable.
- A total of 781 data points is true negative, implying that the classification model labelled

Table 8 Evaluation criteria estimate for random forest

Attribute	Precision	Recall	F1 score	Support
1	0.93	0.67	0.78	61
0	0.97	1.00	0.99	781
Accuracy			0.97	842
Macro average	0.95	0.83	0.88	842
Weighted average	0.97	0.97	0.97	842

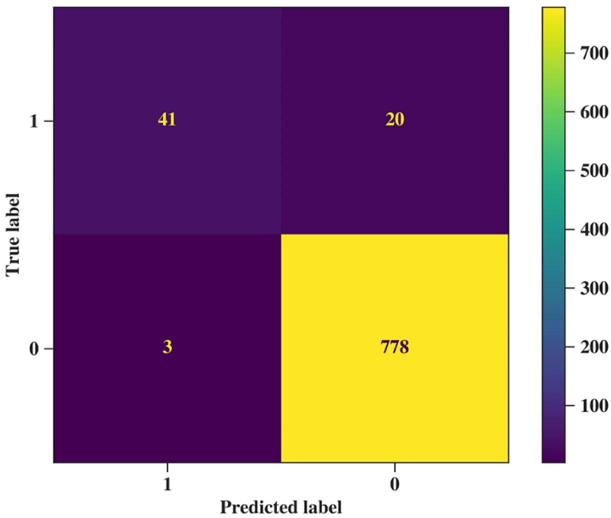

Fig. 8 Confusion matrix for random forest

unstable slopes as unstable.

3.3.2 Random forest (RF)

The RF classification model achieves an accuracy of 0.9881 on the training dataset. This means that the RF model is good enough to classify slope stability problems. The RF classification model for training data correctly predicts 98 out of 100 cases.

The accuracy of the RF classification model on the testing dataset is 0.973. This suggests that the RF model is effective in classifying slope stability problems. The RF classification model for unseen testing data correctly predicts 97 out of 100 cases.

Table 8 shows the details of the classification report for the RF learning classification model. Out of all datasets that the model predicted as unstable, only 97% were unstable. Out of all datasets that the model predicted as stable, 93% were stable. The model correctly predicted 67% of all stable datasets; out of all unstable datasets, the model correctly predicted 100%.

As the F1 score for an unstable slope (0.96) is nearly one, and a stable slope (0.78) is not closer to one, our model prediction is unreliable for a stable slope. However, the F1 score for a stable slope is far lower than that for an unstable slope. The RF classification model predicts unstable slopes more correctly than stable slopes. This model cannot be used for classification, as the prediction for positive data is much lower than other classification models.

The confusion matrix generated by the RF is shown in Fig. 8. From a total of 842 test datasets,

- Forty-one data points are true positive, as the classification model labels stable slopes as stable.
- Twenty data are categorized as false negatives, implying that classified model misclassified stable slopes as unstable.
- Three data points are false positives, implying that the classification model incorrectly classified unstable slopes as stable.
- A total of 778 data points are true negatives, as the classification model labelled unstable slopes as unstable.

3.3.3 Comparison of SVM and RF classification models

The predicted results from the classification models are compared to identify the most effective algorithms and accurately predict the slope class.

The accuracy rates for both the training and testing datasets exceed 90% for both the SVM and RF models. This indicates that both machine learning classification models for slope stability prediction are very effective. The F-1 score of the SVM model is 0.94, and the F-1 score of the RF model is 0.78.

Different performance metrics for machine learning classification models are shown in Table 9. SVM models have a higher accuracy of approximately 0.99, and the RF classification model has an accuracy of 0.93. The precisions for SVM and RF are 0.95 and 0.93, respectively.

Each model is given a prediction score as an evaluation measure, with a greater score given to the model with the best performance indicators. SVM performs better than RF in the overall evaluation, making SVM the preferred choice for classification of slope stability issues.

Table 9 Measurements of classification model's performance in terms of various indicators to evaluate the overall rank of ML models

Performance Indicator	ML Models	SVM	RF
	Accuracy	0.99	0.93
	Precision	0.95	0.93
	F-1 Score	0.94	0.78
	Recall	0.93	0.67
Score	Accuracy	6	1
	Precision	5	3
	F-1 Score	5	2
	Recall	5	2
	Total	21	8
	Overall Rank	2	6

Table 10 Slope datasets from the literature used to compare with the ML model results

Data Source	γ	c	ϕ	θ	H	r_u	Actual FOS
Samui (2008)	16.00	70.00	20.00	40	115.00	0.00	1.11
	20.41	24.90	13.00	22	10.67	0.35	1.40
	19.63	11.97	20.00	22	12.19	0.41	1.05
	21.82	8.62	32.00	28	12.80	0.49	1.03
	20.41	33.52	11.00	16	45.72	0.20	1.28
	18.84	15.32	30.00	25	10.67	0.38	1.33
	18.84	0.00	20.00	20	7.62	0.45	0.85
	19.06	11.71	28.00	35	21.00	0.11	1.09
	18.84	14.36	25.00	20	30.50	0.45	1.11
	18	24.00	30.15	45	20.00	0.12	1.12
	22.40	10.00	35.00	45	10.00	0.40	0.90
Chakraborty and Goswami (2017)	17.40	5.00	43.50	58	29.00	0.05	0.67
	17.80	14.00	44.20	65	31.00	0.07	0.45
	19.80	57.50	41.30	62	23.00	0.19	1.74
	17.60	39.50	30.20	50	38.00	0.04	1.17
	17.30	39.00	30.00	50	35.00	0.04	1.19
	17.80	38.70	30.50	60	26.00	0.00	1.22
	17.90	39.00	31.20	55	25.00	0.15	1.21
	17.30	39.00	30.00	50	26.00	0.20	1.39
	17.30	37.90	30.00	45	29.00	0.37	1.16
	17.50	38.50	29.00	50	33.00	0.20	1.07
	17.50	39.20	29.70	55	31.00	0.00	1.17
	17.80	39.80	31.30	45	32.00	0.34	1.13
	17.30	39.00	30.00	48	30.00	0.03	1.41

4 Discussion

4.1 Model performance

To demonstrated the model's reliability and robustness, the performance evaluation of the developed models is essential. Table 10 consists of 24 slope cases collected from the literature. Datasets from serial numbers 1 to 11 are from Samui (2008) for the United Kingdom and Canada, and datasets from serial numbers 12 to 24 are from Chakraborty and Goswami (2017) for the Jorabat-Shillong Expressway (NH-40) in India. These analytical findings are compared with the outcomes of the prediction models.

The prediction of the FOS from MLR models on real slope datasets is presented with the scatter plot in Fig. 9. The regression plot shows a coefficient of determination value higher than 0.8; hence, all these models are found to have good coherency for predicting the output features. MLR model prediction aligns closely with the observed data from Chakraborty and Goswami (2017), validating the model applicability.

The scatter plot in Fig. 10 shows how an ANN model uses real slope datasets to estimate the FOS. Additionally, the regression figure shows a coefficient of determination that is higher than 0.8. These models thus show their efficiency in predicting the qualities of the output. Similar findings were observed in studies by Gelisli et al. (2015) and Ray et al. (2020) demonstrating effectiveness of ANN in predicting slope stability.

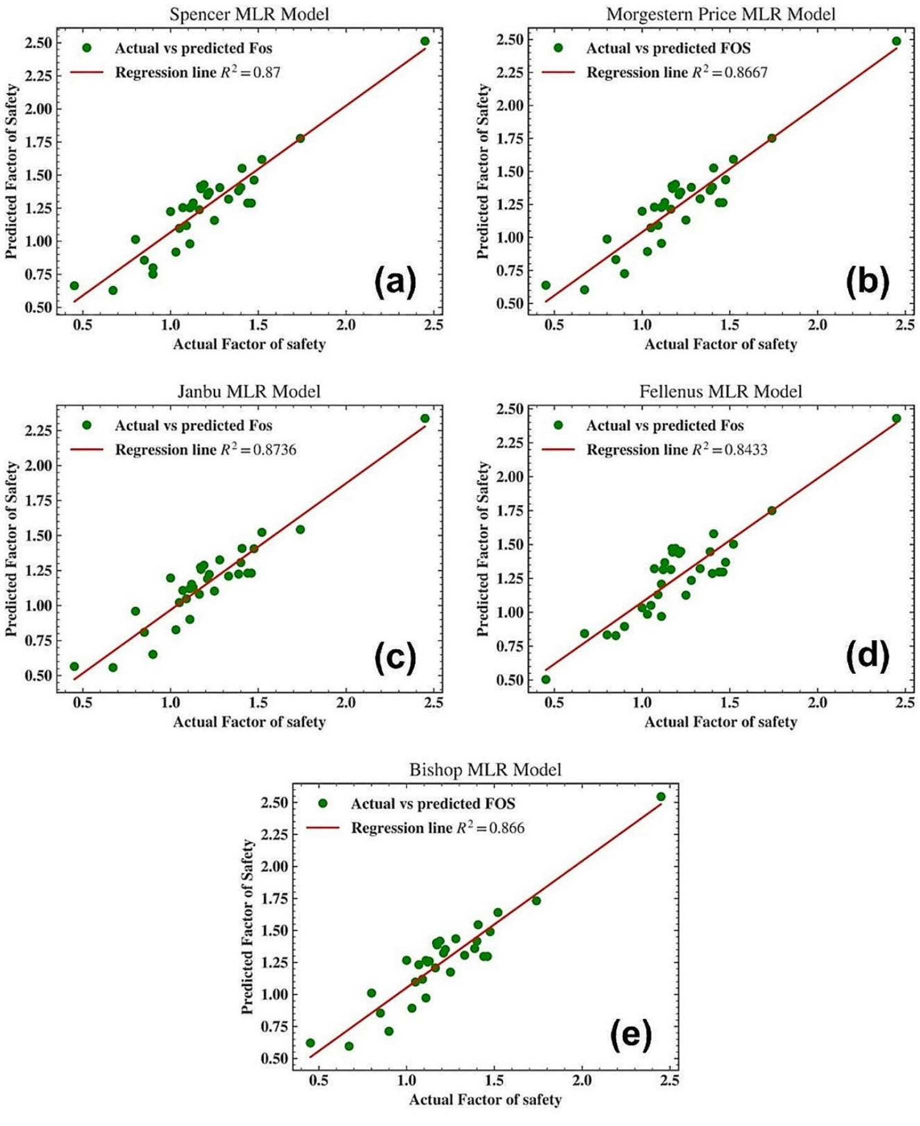

Fig. 9 Prediction of FOS from MLR models on real slope datasets for (**a**) Spencer, (**b**) Morgenstern-Price, (**c**) Janbu, (**d**) Fellenius, and (**e**)Bishop methods

These models can be integrated into geotechnical engineering software and decision-support systems utilized by engineers and planners. By using the ANN model based on Spencer's method, which has proven to be the most reliable, allows for quick and accurate evaluations of slope stability over large areas, reducing the need for extensive soil property data and field investigations. Engineers can apply these models to real-world scenarios, such as roadside slope assessments in regions like Nepal, India, Canada, and the UK. This enhances slope safety, optimizes resource allocation, and promotes sustainability in engineering projects involving soil slopes.

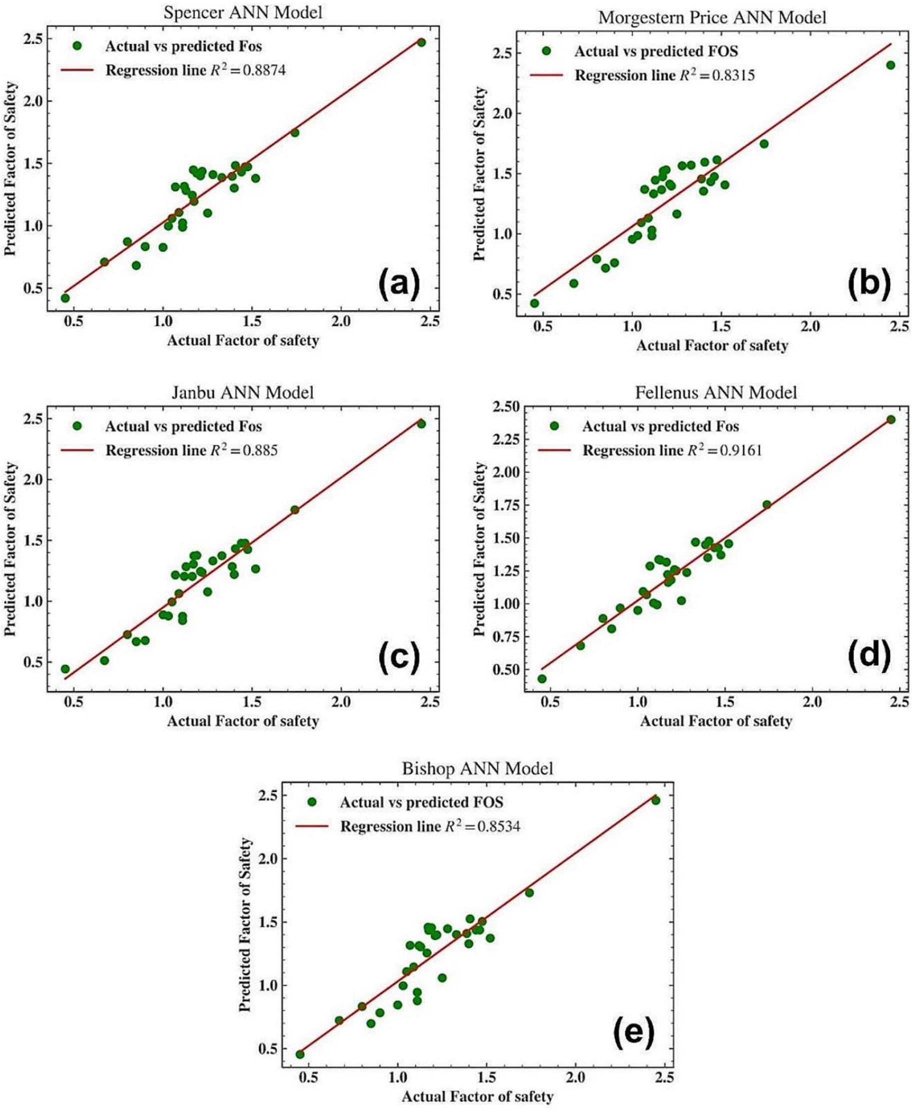

Fig. 10 Prediction of FOS from ANN models on real slope datasets for (**a**) Spencer, (**b**) Morgenstern-Price (**c**) Janbu, (**d**) Fellenius, and (**e**) Bishop methods

Table 11 Roadside slope cases of the Nepal Himalayas considered to compare with the results of ML models

Highway	Location (Northing, Easting)	Soil Description	γ (kN/m^3)	c (kN/m^2)	ϕ(°)	θ (°)	H (m)	FOS (From LEM)	FOS (From ML)
Araniko Highway	27°57'39.26", 85°57'23.92"	Slightly weathered boulders of gneiss and schist with sands	20	0	30	35	27	0.955	0.898
Prithvi Highway	27°50'56.76", 84°39'35.30"	Dark grey, slightly weathered, fine to medium-grained quartzite, cobbles, pebbles.	23	0	32	37	34	0.933	0.912
Kanti Lokpath Highway	27°25'38.41", 85°12'11.63"	Medium-weathered boulders of Phyllite quartzites with sands and gravel	22	0	35	30	15	0.850	0.798
Besisahar-Chame Road	28°15'22.27", 84°22'01.53"	Fine-Grained, very dense, milky white, fresh angular quartzite	24	0	36	34	29	0.915	0.892

4.2 Implementation of the model in Nepal

Nepal, located in the Himalayas, experiences heavy monsoons and steep terrain, which frequently result in landslides (KC et al. 2021; Subedi et al. 2024). This problem is exacerbated by unanticipated road development. The number of roadways tripled between 1990 and 2016, including unofficial roads, because of increased road construction for economic expansion. Landslides and road development expenditures are related in recent studies. In contrast to China, where 7% of fatal construction-related landslides occurred near roadways, 43% did so in Nepal, according to Froude and Petley (2018). These landslides have serious negative effects on society and the economy (McAdoo et al. 2018).

In this scenario, practitioner confidence is low for sophisticated techniques such as FE modelling for analysis of slope stability. There is a critical need for a more straightforward technique for evaluating the FOS of roadside slopes. It should also be functional for on-site engineers. Considering this necessity, we have implemented the ML model results of this study in the Nepal context. Table 11; Fig. 11 show the details of four typical roadside slope failure cases in Nepal. On the basis of data collected from the site and lab test results, FOS values from both LEM and ML were assessed. The results are coherent with each other, signifying the implementation of the model.

Fig. 11 Site locations of four cases of roadside slope failures: (**a**) Araniko highway, (**b**) Prithvi highway, (**c**) Kanti Lokpath highway, and (**d**) Besisahar-Chame road (as shown in detail in Table 10)

5 Conclusion

The availability of comprehensive and reliable datasets is one of the primary challenges with slope stability analysis, particularly when applying machine learning techniques. In this study, we prepared a robust dataset of 4,208 slope cases using limit equilibrium-based Slide software which included six key soil parameters (c, H, ϕ, γ, θ, *and* r_u). This dataset split into 80% as training dataset and 20% as testing dataset encompasses a wide range of slope geometries and material properties. While the dataset supports model training and validation, variation in geological, environmental, or geographical conditions could affect its real-world applicability and predictive accuracy. The FOS values estimated by the Bishop, Fellenius, Janbu, Morgenstern-Price, and Spencer methods were used to model both multi linear regression (MLR) and artificial neural network (ANN). The classification models (i.e., random forest (RF) and support vector machine (SVM)) were adopted to predict the output for unseen data. R^2 and MAE are used for both the training and testing datasets to evaluate the prediction performance of the models. The performance of the models was validated by comparing the predicted outcomes with roadside slopes from different locations in Nepal, India, Canada, and the UK. Based on the results obtained, we draw the following conclusions.

- ANN and MLR shows effectiveness in analysing stability of slopes.
- The MLR model for the bishop method predicts most accurately, with a regression coefficient of 0.948, and the performance of the other models is also good, with an R^2 value exceeding 0.9.
- The ANN model for the Spencer technique yields the most precise predictions, with regression coefficients of 0.966 and 0.973 for the training and testing datasets, respectively.
- The accuracy of the classification model is 0.929 and 0.992 for RF and SVM, respectively.
- The ANN model developed for all methods surpasses the prediction performance over the MLR model in all cases.

Overall, the methodology utilized to assess slope stability in terms of FOS would be beneficial in the field of decision-making for engineers. This study advances mitigation, design, and early warning systems by offering more accurate predictive models and optimizing design parameters. Compared to previous research, machine learning offers greater precision, adaptability, and efficiency in addressing natural disasters and hazards. The findings demonstrates that the ANN model, based on Spencer's method, provides the highest reliability, offering new insights for simplified decision-making in slope safety and enhancing sustainability in engineering projects. These findings highlight the potential of ML techniques to improve the accuracy and efficiency of slope stability assessments compared to earlier studies. This study does, however, have certain limitations, such as its reliance on a dataset created with Slide software, which may not fully capture the complexities of real-world slope conditions. The models developed, including MLR, ANN, RF, and SVM, depend on the quality and representativeness of this dataset. While the study validated these models with roadside slope cases in Nepal, India, Canada, and the UK, this may not encompass all geographical and geological variations, potentially limiting the generalizability of the findings. These models might need recalibration and more data to be applicable in different regions or conditions, necessitating further research and adaptation for broader use.

Author contributions Conceptualization, RK and MA; methodology, RK, MA, and KS; software and coding, RK and MA; validation, RK, MA, KS, IPA, and NPB; formal analysis, MA, and RP; investigation, RK; data curation, RK, MA, and RP; writing—original draft preparation, RK, MA, and RP; writing—review and editing, KS, IPA, and NPB; supervision, KS, IPA, and NPB. All authors have read and agreed to the published version of the manuscript.

Funding The authors did not receive any funding for this research.

Data availability The datasets used and/or analysed during this work are accessible upon reasonable request from the corresponding author.

Declarations

Competing interests The authors have disclosed that they have no possible conflicts of interest related to the research, writing, or publishing of this paper.

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