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# Enhanced Earth Slope Stability Assessment Using Computational Intelligence Algorithms

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**Abstract** Proper slope stability prediction, particularly in mountainous terrains, is essential to reduce the catastrophic consequences of failures. Calculating the factor of safety (FS) with traditional methods is challenging and requires either tedious computations or sophisticated software. Advancements in machine learning (ML) methods and data collection have substantially improved slope stability analysis. While many ML algorithms have been applied to evaluate slope failures, there is a lack of a comprehensive comparative analysis across these algorithms with a broad dataset. This study employed classical and ML procedures to classify and predict the FS required for geotechnical design. Novel models were developed using a large dataset that included different soil and geometric attributes. The FS was modeled in terms of soil unit weight, cohesion, friction angle, slope angle and height, and pore water pressure ratio, using Python. Eight statistical metrics and confusion matrix measures were employed to evaluate the reliability of the models. The results showed that ML models were effective in predicting and classifying the FS, with the random forest model demonstrating optimal performance in terms of accuracy for both regression and classification models. The model's applicability was further confirmed with an independent validation dataset. Sensitivity analysis results indicated that soil cohesion was the most influential parameter on the FS, while slope height had the least impact. The illustrative example demonstrated the direct implementation of the model compared to traditional solutions. The findings of this study assist practitioners in estimating the FS required for the preliminary assessment of slope failure and in selecting appropriate protective measures and mitigation techniques. This can lead to better decision-making, optimized design processes, and increased sustainability for geotechnical and highway projects involving earth slopes.

**Keywords** Slope Stability, Factor of Safety, Computational Intelligence Algorithms, Machine Learning, Classification, Sensitivity Analysis

## 1. Introduction

Slope instability, including landslides, mudslides, and ground subsidence, is a critical factor to consider for the safe design in geotechnical engineering. Slopes are commonly encountered in highway and geotechnical projects, including road facilities, earthen structures, railway lines, mining site pits, and earth dams. Proper engineering countermeasures are essential for the safe operation of these projects.

Generally, slope failures occur gradually and can lead to serious and catastrophic disasters. These failures can damage public properties, infrastructure facilities, railways, and foundation systems, resulting in significant economic consequences. The problem is exacerbated when these failures happen in densely populated residential areas, leading to fatal losses.

Slope stability evaluation is critical for risk assessment and safe operation of infrastructure projects. It can be assessed based on initial data obtained during field or laboratory experiments through site investigation. Ensuring slope safety involves calculating the forces and stresses acting on a slope to determine its ability to withstand these forces on a potentially unstable surface (Figure 1). The safety factor (FS) represents the balance between total resisting forces or moments and disturbing forces or moments, as illustrated by Equation 1.

$$\mathrm{FS} = \frac{\sum \text{Resisting forces (or momenets)}}{\sum \text{Disturbing forces (or momenets)}} \tag{1}$$

A reliable determination of the minimum FS is a crucial issue in geotechnical engineering, as its value is used to implement appropriate stabilization strategies [1]. Various analytical methods have been developed to determine the failure mechanism, probable failure surface, and instability scale. Traditional techniques such as limit equilibrium methods (LEM) with circular/non-circular slip surfaces are widely used due to their minimal required assumptions and their balance between computational simplicity and accuracy [2]. Advancements in computer applications for slope stability analysis have significantly improved the efficiency of these methods, allowing for more accurate determination of slope FS with the help of sophisticated software.

Finite element methods (FEM) are commonly used as rigorous and more representative alternatives to provide a detailed assessment of slope behavior [3]. Typically, the shear strength reduction method (SSRM) is incorporated with the FEM to analyze slope stability. Incorporating the SSRM with the FEM allows for a detailed evaluation of slope behavior in the field through the simulation of elastic-plastic and stress-strain relationships of soil. The process involves incrementally decreasing soil shear strength parameters until failure is identified. In the SSRM, the friction angle and cohesion are reduced by a common coefficient. The effective friction angle and cohesion are then used in the analysis to identify the critical slope failure. Incorporating FEM with the SSRM offers a reliable determination of the failure state in terms of size, shape, and location, resulting in an accurate estimation of the FS for infrastructure projects built on earth slopes.

With the booming growth of large-scale infrastructure and the expansion of industrial projects on mountainous terrains, involving many slopes, a careful assessment of slope safety prior to project construction is required to select the most appropriate and feasible engineering mitigation method. During the preliminary design stage of a project, it is crucial to conduct a simple, rapid, and accurate assessment, especially in areas prone to collapse, where large excavations are necessary and intense rainfalls within a short period of time are anticipated.

To address this task, advanced computationally intelligent methods have been widely applied in geo-engineering. Recent examples include machine learning (ML) algorithms that are used to reasonably detect the nonlinear complex relationships between the FS and its possible influential parameters, such as soil and geometric properties, and pore water pressure ratio, based on previous data [4].

ML algorithms provide promising, straightforward, and cost-effective solutions for addressing natural disasters and hazards in civil engineering. Due to their adaptability, precision, and efficiency, they have been successfully used in several areas of geotechnical engineering to develop robust and reliable predictive models. Key applications cover a wide range, including mechanical property estimation, soil categorization, settlement of soil, sidewall displacement of underground structures, field description, deep foundation design, tunnel surface settlement, physical property determination [5], and slope engineering [6]. By utilizing large datasets of slope behavior, including geological and geotechnical data, ML techniques can effectively and rapidly analyze and capture the complex nonlinear interactions between various inputs within a dataset, minimizing the effort needed to determine the FS. These ML methods offer a valuable initial assessment of slope safety and should be further validated through a professional analysis.

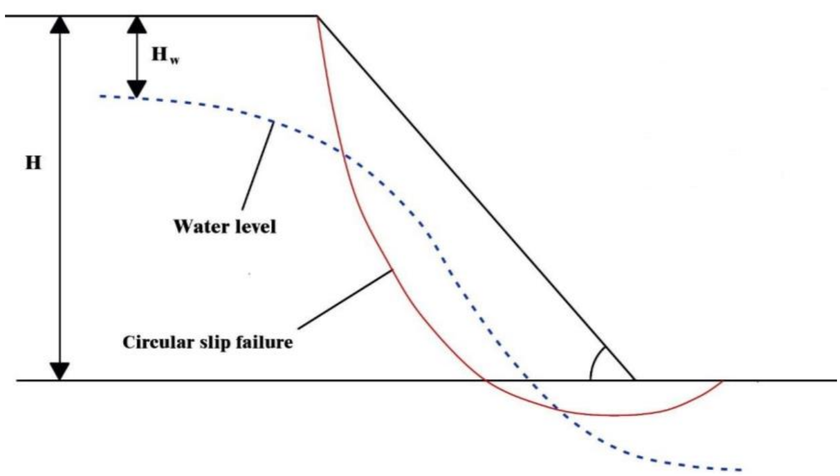



**Figure 1.** Schematic sketch of a typical earth slope with a potential failure mechanism

Scholars employed numerous ML techniques to predict the FS for slope stability, providing favorable results and new methodologies for evaluating this parameter. For instance, Yang [4] employed various models, including decision tree regression, linear discriminant analysis, and support vector machine, to classify and predict the FS for slope stability, presenting a new and promising methodology for determining slope safety in geotechnical engineering. Samui [7] employed support vector machines to characterize the stability state of slopes through classification and regression techniques. Erzin and Cetin [8] used artificial neural networks and multiple regression models to estimate FS for natural slopes. Das [9] employed various artificial neural network models to assess FS and categorize its stability as either stable or unstable. Several artificial neural networks were proposed by Abdalla [10] to estimate the FS for slope failure in clayey soils. Ray [11] employed an artificial neural network model to effectively assess the safety of Himalayan slopes. Gordan [12] estimated slope stability during earthquakes using artificial neural networks and particle swarm optimization methods. Hoang and Pham [13] conducted an analysis of slope stability estimation employing extreme learning machines, the least squares support vector machines, and radial basis function neural networks. Ahmad [14] determined the FS for slopes using a novel tree-augmented Naive-Bayes model. Bai [15] employed ML techniques to identify the potential association between geological characteristics and slope performance in harsh environments, facilitating an accurate evaluation of slope safety. The equilibrium optimization method and the vortex search algorithm were used by Foong and Moayedi [16] to improve a neural network model that accurately estimated the FS for earth slopes.

While the literature review found that researchers have used computationally intelligent methodologies to analyze and identify earth slope instability and have recommended valuable models, there are still some concerns that need to be appropriately addressed.

1) The available ML models were developed based on small datasets or specific soil types. As shown in Table 1, a survey of selected studies indicated that the size of the datasets used was relatively small [1, 7, 9, 17-21]. Additionally, the proposed models may not be optimal as they offer customized solutions for specific slopes. Consequently, such models may not adequately address all slopes. Thus, using these models for different soil configurations is questionable.

**Table 1.** Selected studies on ML-based slope stability predication

| Reference | ML algorithm | Records |
|---|---|---|
| Sakellariou and Ferentinou [1] | BPNN | 46 |
| Samui [7] | SVM | 46 |
| Das [9] | ANN | 46 |
| Feng [17] | NBC | 82 |
| Liu [18] | ELM | 97 |
| Lu and Rosenbaum [19] | BPNN | 32 |
| Rukhaiyar [20] | PSO–ANN | 83 |
| Xue [21] | PSO–SVM | 46 |

2) A comprehensive comparison of ML methods in terms of their effectiveness and efficiency in predicting slope instability has not been well investigated. There is a lack of a simultaneous systematic comparison of ML modeling techniques, with no clear recommendations for the most effective one to apply. Furthermore, investigators did not explicitly provide the codes for their proposed models, making the use of such models in geotechnical applications difficult.

3) Limited ML algorithms have been employed in stability calculation, ignoring new and advanced procedures.

4) In some studies, the reliability of the proposed models' predictions has not been validated with independent datasets. Thus, it is unknown whether these models are valid for other slope instability cases.

5) A clear identification of the most and least influential parameters across a set of variables (sensitivity analysis) among different ML methods has not been fully examined.

Given the challenges associated with traditional iterative methods to determine the FS, the constraints on available models, and the absence of a comprehensive, widely accepted modeling approach and models to predict the slope FS, it would be beneficial to develop reliable models that can directly predict the FS for slope failure. The availability of well-calibrated, robust prediction models is critical for estimating the FS value for failure assessment and determining the appropriate stabilization methods for critically unsafe slopes.

The objectives of this study are to 1) develop diverse, yet reliable, and comprehensive models for estimating FS based on soil and geometric characteristics, leveraging advanced ML computational algorithms to increase the precision and reliability of estimates over traditional methods; 2) evaluate the effectiveness of various modeling techniques using a larger set of data than previously employed; and 3) examine the rationality of the suggested models in relation to independent validation results.

To achieve these objectives, a sizable and comprehensive model-building dataset was sourced from existing literature. Eight modeling techniques were used to predict the FS using six input parameters. Eight statistical performance metrics and the confusion matrix were employed to assess the regression and classification efficiency of the suggested models with recommendations for the optimum one.

# 2. Methodology

## 2.1. Investigation Layout

As illustrated in Figure 2, the two-year research program was split into five parts. The first part involved a comprehensive review of professional literature on the evaluation of FS for slope stability using advanced ML algorithms, along with the collection of data for the model-building dataset. The second part focused on developing and ranking regression and classification models as well as recommending the optimum model. The third part consisted of validating the suggested model using a separate validation dataset. The fourth part involved conducting a sensitivity analysis to categorize the most and least critical parameters affecting FS. The fifth part included the study findings and conclusions.

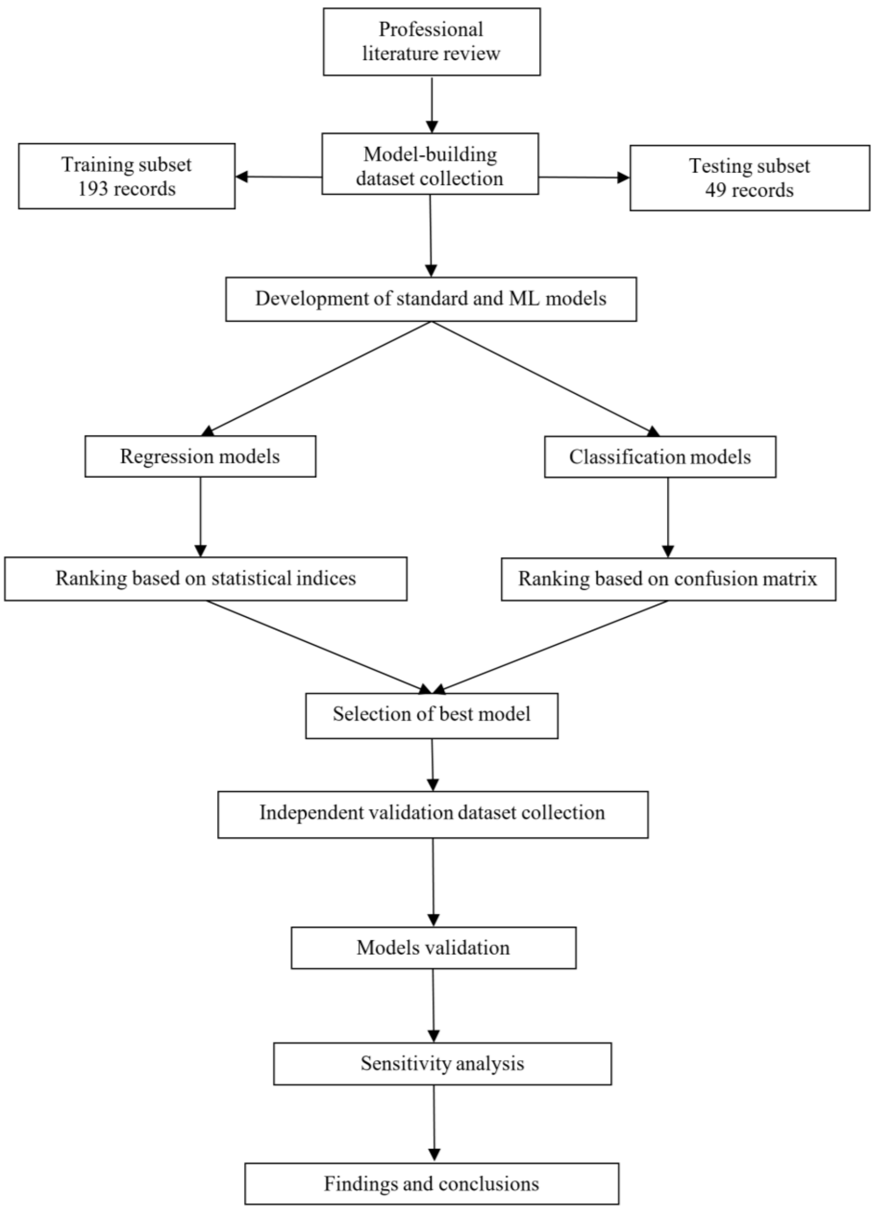



**Figure 2.** Research program flowchart

## 2.2. Geotechnical Dataset Development

The major goal of the current investigation is to assess the application of diverse ML techniques for slope assessment. To achieve this, a primary model-building dataset (242 records) was collected from 14 references covering an extensive range of geometric and soil parameters [1, 22-34].

Past investigations and data availability have indicated that terrain landforms, soil physical properties, and hydrogeological conditions are identified as the most effective parameters affecting the FS for slope stability. As illustrated by Equation 2, the six properties selected in this research are as follows: 1) soil unit weight ($\gamma$) refers to the soil weight per unit volume, 2) soil cohesion (C) defines the component of shear strength that is independent of the vertical effective pressure at failure, 3) soil friction angle ($\emptyset$) quantifies the soil's capacity to resist movement on a slippery surface, 4) slope angle ($\beta$) refers to the inclination of the slope relative to the base plane, 5) slope height (H) represents the vertical distance between the base of the slope and its crest, and 6) pore water pressure ratio ($r_u$) is the ratio of water pressure to normal effective stress, ranging between zero and one, where zero represents a dry state and one indicates a saturated state.

$$\mathrm{FS} = \mathrm{f}(\gamma,\ \mathrm{C},\ \emptyset,\ \beta,\ \mathrm{H},\ r_u) \tag{2}$$

The Pearson correlation matrix is used to check the association between parameters and to detect potential redundancies within the entire dataset. As shown in Table 2, Pearson's correlations were determined based on the model-building dataset. The correlation coefficients indicate a positive association between the FS and unit weight, cohesion, and friction angle, meaning that an increase in these variables leads to larger values of the FS. Conversely, when the slope angle, slope height, and pore water pressure ratio increase, FS decreases. Additionally, there were no substantial correlations, positive or negative, across the input parameters, with no redundant ones allowing the use of these parameters for models' development.

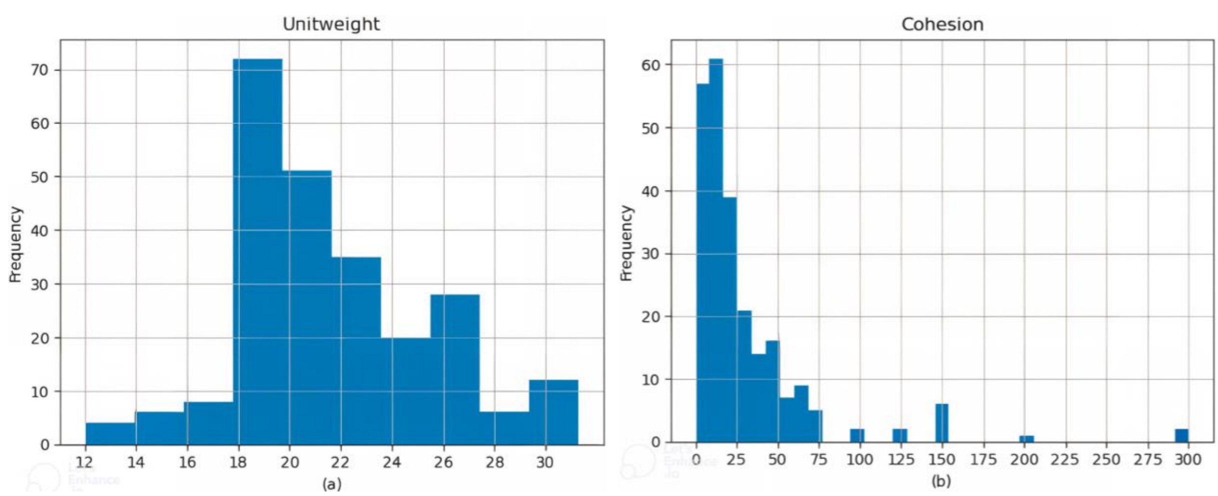
**Table 2.** Pearson correlation matrix

| | $\gamma$ | C | ø | $\beta$ | H | $r_u$ | FS |
|---|---|---|---|---|---|---|---|
| $\gamma$ | 1 | 0.45 | 0.54 | 0.52 | 0.65 | 0.10 | 0.13 |
| C | | 1 | 0.33 | 0.45 | 0.27 | 0.02 | 0.11 |
| ø | | | 1 | 0.61 | 0.33 | 0.12 | 0.33 |
| $\beta$ | | | | 1 | 0.31 | 0.07 | -0.04 |
| H | | | | | 1 | 0.01 | -0.08 |
| $r_u$ | | | | | | 1 | -0.14 |
| FS | | | | | | | 1 |

Based on the descriptive characteristics of the model-building dataset in Table 3, the mean value for the FS was 1.31 with a standard deviation of 0.37. The lowest and highest values were 0.63 and 2.31, respectively. Histograms of parameters were created to assess the validity of data records, as shown in Figure 3. Since the distributions of the variables exhibited a near-normal distribution, and were adequately wide, the data were consequently employed to construct the models.

**Table 3.** Statistical features of the model-building dataset

| | $\gamma$ (kN/m$^3$) | C (kN/m$^2$) | ø (degree) | $\beta$ (degree) | H (m) | $r_u$ | FS |
|---|---|---|---|---|---|---|---|
| Count | 242.00 | 242.00 | 242.00 | 242.00 | 242.00 | 242.00 | 242.00 |
| Mean | 21.63 | 29.71 | 27.37 | 35.00 | 102.46 | 0.18 | 1.31 |
| SD | 4.09 | 39.73 | 10.77 | 10.30 | 125.65 | 0.15 | 0.37 |
| Min | 12.00 | 0.00 | 0.00 | 16.00 | 3.60 | 0.00 | 0.63 |
| Max | 31.30 | 300.00 | 45.00 | 65.00 | 565.00 | 0.50 | 2.31 |



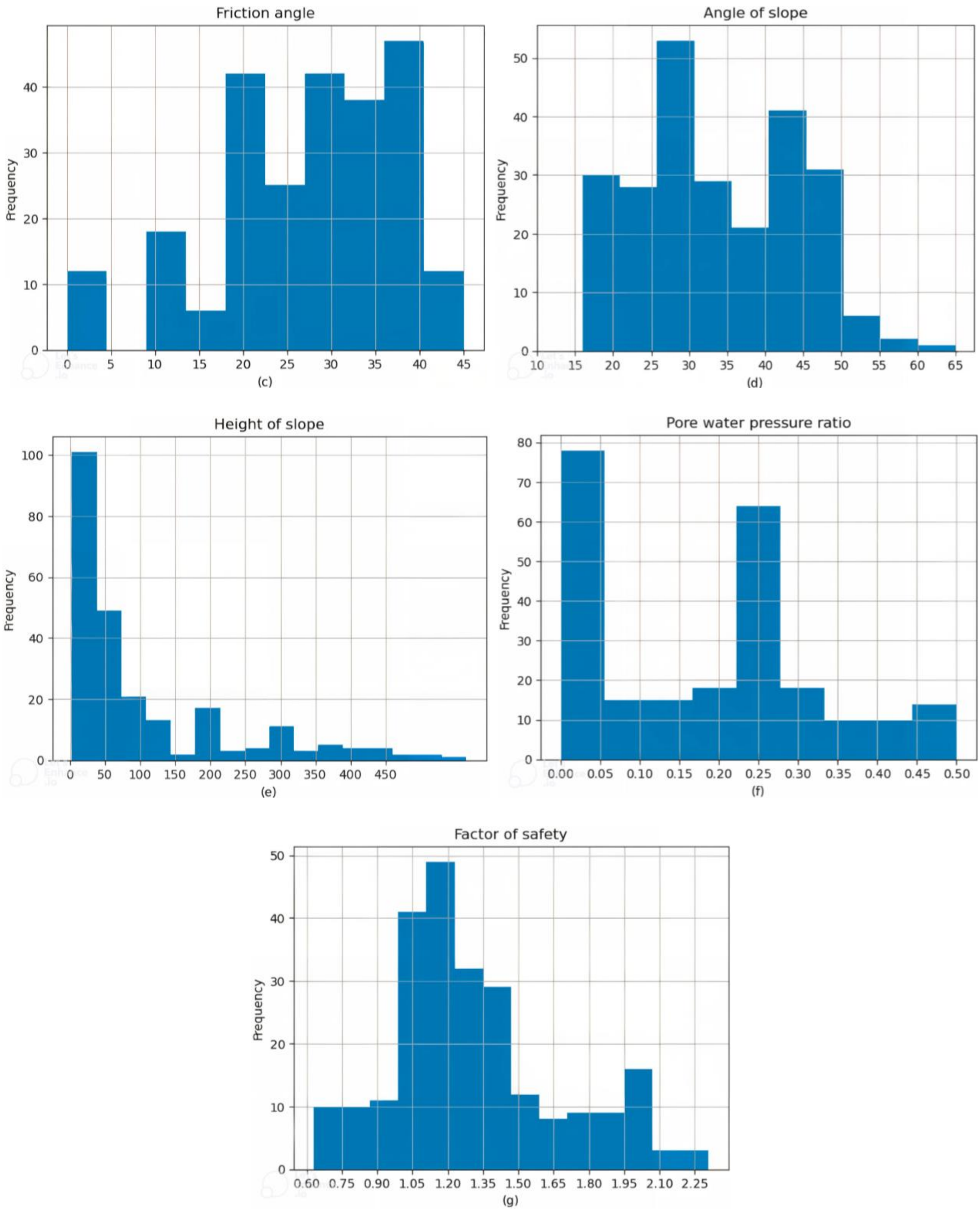



**Figure 3.** Histogram of the model-building dataset: (a) Unit weight, (b) Cohesion, (c) Friction angle, (d) Slope angle, (e) Height of slope, (f) Pore water pressure ratio, and (g) Factor of safety

To guarantee model effectiveness, the model-building dataset was split into two distinct subsets. The training subset is utilized to allow algorithms to recognize patterns and relationships in existing data, thus allowing accurate predictions and classifications. The testing subset is used for testing the algorithms and is not visible to the training subset. Its goal is to measure the generalization strength of the training model. In this investigation, the model-building dataset was randomly split into 193 records (80%) as a training subset and 49 records (20%) as a testing subset. Model implementation was carried out with Python programming language.

### 2.3. Brief Description of Regression and Classification Techniques

Eight methods were selected for this investigation to predict the FS, including two traditional regression and six ML methods. The methods were selected based on their widespread use in engineering and their excellent predictive performance for both regression and classification problems. Below is a brief overview of each model, with detailed descriptions available in the cited references.

1) Linear regression (LR) is a fundamental regression method employed to define the link between a dependent variable and several independent variables. It seeks to identify a linear relationship that precisely characterizes the connection between the variables, facilitating predictions and comprehension of how changes in the independent variables impact the dependent variable [35].

2) Polynomial regression (PR) is a kind of regression analysis that uses a polynomial equation to characterize the relation between a dependent variable and many independent variables when such a relationship is non-linear but can be expressed by a polynomial equation. It enhances linear regression by accommodating more flexible and nonlinear relationships between variables [36].

3) The decision tree (DT) is a widely used ML approach for classification and regression tasks. It can generate predictions from data, by building a tree-like model of decisions with their possible outcomes. The decision-making process resembles a tree structure with branches and nodes where each node implies a choice based on a particular aspect or attribute of the data. Moreover, it is successful with both quantitative and qualitative data. It can manage large datasets and is appropriate for incorporating non-linear correlations among variables [37].

4) Random forest (RF) is a popular ML algorithm mainly used for regression and classification applications. It is formed by combining many distinct decision trees to provide a robust forecasting model. The dataset is split into many sample subsets using the bagging technique. Each sample subset is trained individually using a random selection of characteristics rather than the whole, enhancing variability across the decision trees via the Bootstrap approach. Random Forest often offers superior accuracy relative to an individual decision tree model while preserving some advantageous characteristics of tree models [38].

5) The support vector machine (SVM) is used for classification and regression tasks [39]. Its goal is to identify the ideal hyperplane, placed to maximize the boundary between two classes. The primary mechanism of SVM is the transformation from non-linear to linear spaces. This methodology has been used across several areas of engineering.

6) K-nearest neighbor (KNN) is a commonly used ML technique for classification and regression tasks. It is classified as instance-based or lazy learning algorithms, as it does not construct a model during training; instead, it retains the complete training dataset for prediction purposes [40]. The "K" in KNN denotes the quantity of the nearest neighbors selected during prediction and is a hyperparameter selected before implementing the algorithm.

7) Deep neural network (DNN) is a category of artificial neural network (ANN) modeling, motivated by the architecture of the human brain [41]. Its objective is to identify complex patterns and relationships within datasets to simulate system behavior. In DNN, the word "deep" refers to the existence of numerous layers stacked sequentially, enabling the model to acquire hierarchical representations of the data. Each layer consists of artificial neurons that process information and pass it on to the next layer. These neurons are connected through adjustable parameters called weight functions and bias units, which are learned during the training operation. To introduce flexibility and enable them to approximate complex functions, DNN uses non-linear activation functions. Input data are passed through the layers to generate predictions, which are compared to the actual values using an activation function (forward propagation). Next, the model adjusts its parameters iteratively using backpropagation to improve its performance. The depth and complexity of DNNs make them powerful tools for solving advanced classification and regression engineering problems.

8) Naïve Bayes (NB) is an ML technique frequently employed for classification tasks. The technique is linked to Bayes' theorem and considers most variables independently. This assumption streamlines the calculation and enhances the computational efficiency of the algorithm, even when managing numerous features [17]. NB can be utilized or trained on limited datasets and is capable of delivering predictive outcomes in real time. The NB approach aids in class categorization, enabling the utilization of results, particularly in large-scale data.

### 2.4. Performance Assessment Criteria

#### 2.4.1. Statistical Indices

The performance of models is assessed objectively through a regression analysis comparing predicted and actual results. Eight performance statistics were used to evaluate the strength of the models. These are the Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Coefficient of Determination ($R^2$), Bias Factor (K), Ranking Index (RI), and Ranking Distance (RD).

Model performance is considered excellent when MAE, MSE, RMSE, and MAPE values are close to zero and when the $R^2$ value is close to one. Equation 3 defines the bias factor K as the ratio between the predicted $FS_p$ and actual $FS_a$.

$$K = \frac{FS_p}{FS_a} \quad (3)$$

Underestimation is indicated by a K value less than one, while overestimation is indicated by a K value greater than one. A neutral model with no underestimation or overestimation requires the proportion of K values less than one to be between 40 and 60 percent. The RI is an indicator used to assess model predictions [42], providing valuable statistical information on the model's accuracy and precision, with lower values indicating improved prediction quality (preferably = 0). On the other hand, Cherubini and Orr [43] recommend using RD to evaluate a model's predictive capability, where accuracy and precision are equally weighted. A low RD value (preferably = 0) indicates higher model performance. Precision measures the closeness of predicted values to each other, while accuracy measures their closeness to the correct values. These two measures precision and accuracy are independent of each other.

2.4.2. Confusion Matrix

The efficiency of categorization models is assessed by the confusion matrix, which is a tabular format that facilitates the display of the ML model's performance, as shown in Table 4. Rows in the matrix represent instances of an actual class, while columns indicate instances of an estimated class. These rows and columns specifically represent the quantities of false negatives, true positives, true negatives, and false positives.

**Table 4.** Confusion matrix

| | Classification | Predicted Negative | Predicted Positive |
|---|---|---|---|
| Actual Positive | Stable (1) | False Negative | True Positive |
| Actual Negative | Unstable (0) | True Negative | False Positive |

The effectiveness of the predictive model is measured by four key values: precision, recall, F1-score, and accuracy. The positive predictive value of ‘precision’ represents the proportion of relevant occurrences among selected instances, while the proportion of relevant instances successfully selected is represented by ‘recall’. The ‘F1-score’ is the symmetric average of ‘accuracy’ and ‘recall’ which averages the two metrics, while the ratio of the sum of true positives and negatives to the total number of examined instances is defined as ‘accuracy’.

Further details regarding the modeling techniques and assessment measures used in this study, which are beyond the scope of this article, are available in many references, including those cited above.

# 3. Results and Discussion

### 3.1. Regression Models

Seven regression models were developed to determine the FS, with hyperparameter results presented in Table 5.

The results from the training subset, as presented in Table 6, indicated that the LR and PR models performed poorly due to their relatively high errors when compared to the ML models DT, RF, SVM, KNN, and DNN. Therefore, LR and PR models were not appropriate for estimating the FS.

The $R^2$ value ranged from 0.322 (LR model) to 0.999 (DT, RF, and KNN models), with an average value of 0.8214. The average percentage of K values below one ranged from 41.30% to 58.69%. Therefore, for all regression models, the conversation level remained neutral, neither overestimating nor underestimating the FS. RI values ranged from 0.0009 (RF and KNN models) to 0.3320 (LR model), with an average value of 0.1235. RD values varied between 0.0008 (RF and KNN models) and 0.2670 (LR model), with an average value of 0.0958.

Among the seven regression models, namely LR, PR, DT, RF, SVM, KNN, and DNN, the RF and KNN models demonstrated the highest accuracy, with an $R^2$ value of 0.999, a neutral K percentage of 41.30% and 54.34%, and the lowest RI and RD values of 0.0009 and 0.0008, respectively.

Statistical results from the testing subset, as presented in Table 7 and Figure 4, indicated that LR and PR models performed poorly due to the relatively high errors as compared to ML models DT, RF, SVM, KNN, and DNN. Therefore, LR and PR models were not suitable for determining FS.

**Table 5.** Tuning parameters for the regression models

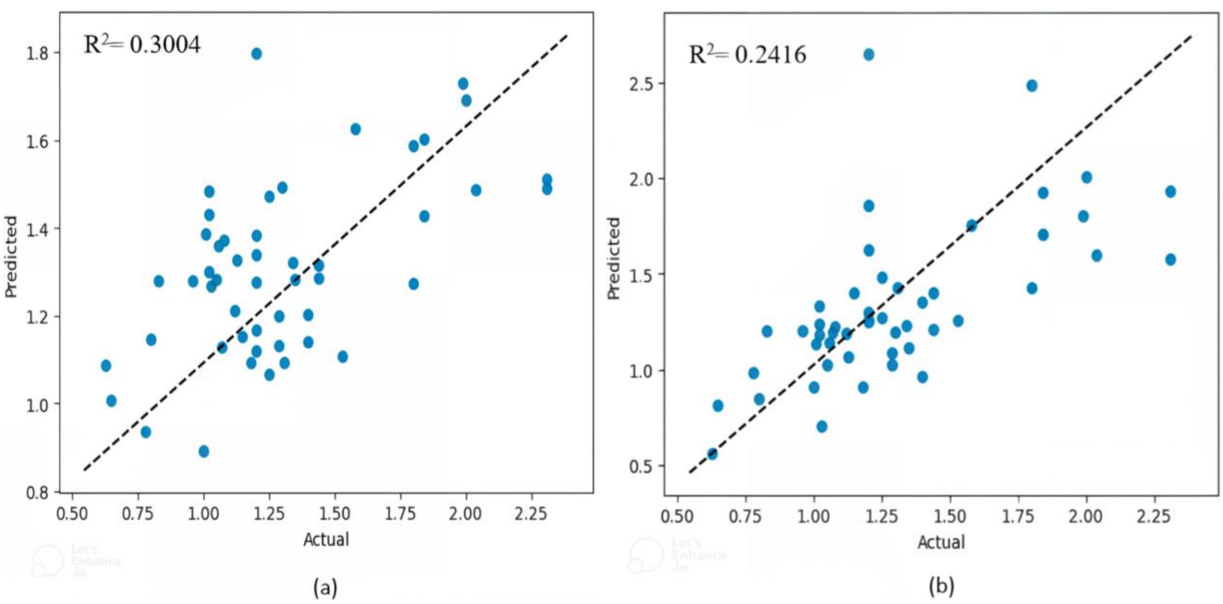
| Model | Hyperparameter |
|---|---|
| Linear regression | - |
| Polynomial regression | Degree = 2 |
| Decision tree | CV =5, n_iter = 200, Max. depth = 14, Min. samples leaf = 1, Random state = 42 |
| Random forest | CV =3, n_iter = 200, Max. depth = 30, Min. samples leaf = 1, Random state = 80, n_ estimators =30, bootstrap = False |
| Support vector machine | CV =3, n_iter = 100, Kernel = rbf, C= 4.97, random state =42 |
| K-nearest neighbor | n_ neighbors = 3 |
| Deep neural network | # Hidden layer =3, # nodes in each layer = 7, 5, 5, 1, activation function = relu, optimizer algorithm = Adam, epochs =1400, batch size= 60 |

**Table 6.** Statistical performance of the regression models (Training subset)

| Model | MAE | MSE | RMSE | MAPE | $R^2$ | %K< 1 | RI | RD |
|---|---|---|---|---|---|---|---|---|
| Linear regression | 0.261 | 0.102 | 0.320 | 0.213 | 0.322 | 52.17 | 0.332 | 0.267 |
| Polynomial regression | 0.158 | 0.039 | 0.199 | 0.130 | 0.688 | 47.82 | 0.227 | 0.173 |
| Decision tree | 0.036 | 0.004 | 0.063 | 0.029 | 0.999 | 42.85 | 0.006 | 0.006 |
| Random forest | $1.04*10^{-4}$ | 1.10-6 | 0.001 | $8.6*10^{-5}$ | 0.999 | 41.30 | $9*10^{-4}$ | $8*10^{-4}$ |
| Support vector machine | 0.080 | 0.015 | 0.126 | 0.068 | 0.876 | 43.47 | 0.148 | 0.115 |
| K-nearest neighbor | 0.0001 | $1*10^{-6}$ | 0.001 | $8.6*10^{-5}$ | 0.999 | 54.34 | $9*10^{-4}$ | $8*10^{-4}$ |
| Deep neural network | 0.092 | 0.017 | 0.130 | 0.075 | 0.867 | 58.69 | 0.150 | 0.108 |
| Average | 0.0896 | 0.0253 | 0.1200 | 0.0736 | 0.8214 | 48.66 | 0.1235 | 0.0958 |

**Table 7.** Statistical performance of the regression models (Testing subset)

| Model | MAE | MSE | RMSE | MAPE | $R^2$ | %K< 1 | RI | RD |
|---|---|---|---|---|---|---|---|---|
| Linear regression | 0.250 | 0.089 | 0.299 | 0.208 | 0.300 | 51.02 | 0.335 | 0.267 |
| Polynomial regression | 0.236 | 0.114 | 0.339 | 0.185 | 0.241 | 54.34 | 0.317 | 0.267 |
| Decision tree | 0.111 | 0.027 | 0.165 | 0.094 | 0.857 | 40.81 | 0.169 | 0.130 |
| Random forest | 0.095 | 0.019 | 0.139 | 0.074 | 0.875 | 43.47 | 0.142 | 0.101 |
| Support vector machine | 0.142 | 0.039 | 0.196 | 0.114 | 0.744 | 59.18 | 0.213 | 0.154 |
| K-nearest neighbor | 0.120 | 0.036 | 0.192 | 0.091 | 0.756 | 43.47 | 0.192 | 0.136 |
| Deep neural network | 0.135 | 0.031 | 0.178 | 0.105 | 0.789 | 69.38 | 0.194 | 0.142 |
| Average | 0.156 | 0.051 | 0.215 | 0.124 | 0.651 | 51.66 | 0.223 | 0.171 |



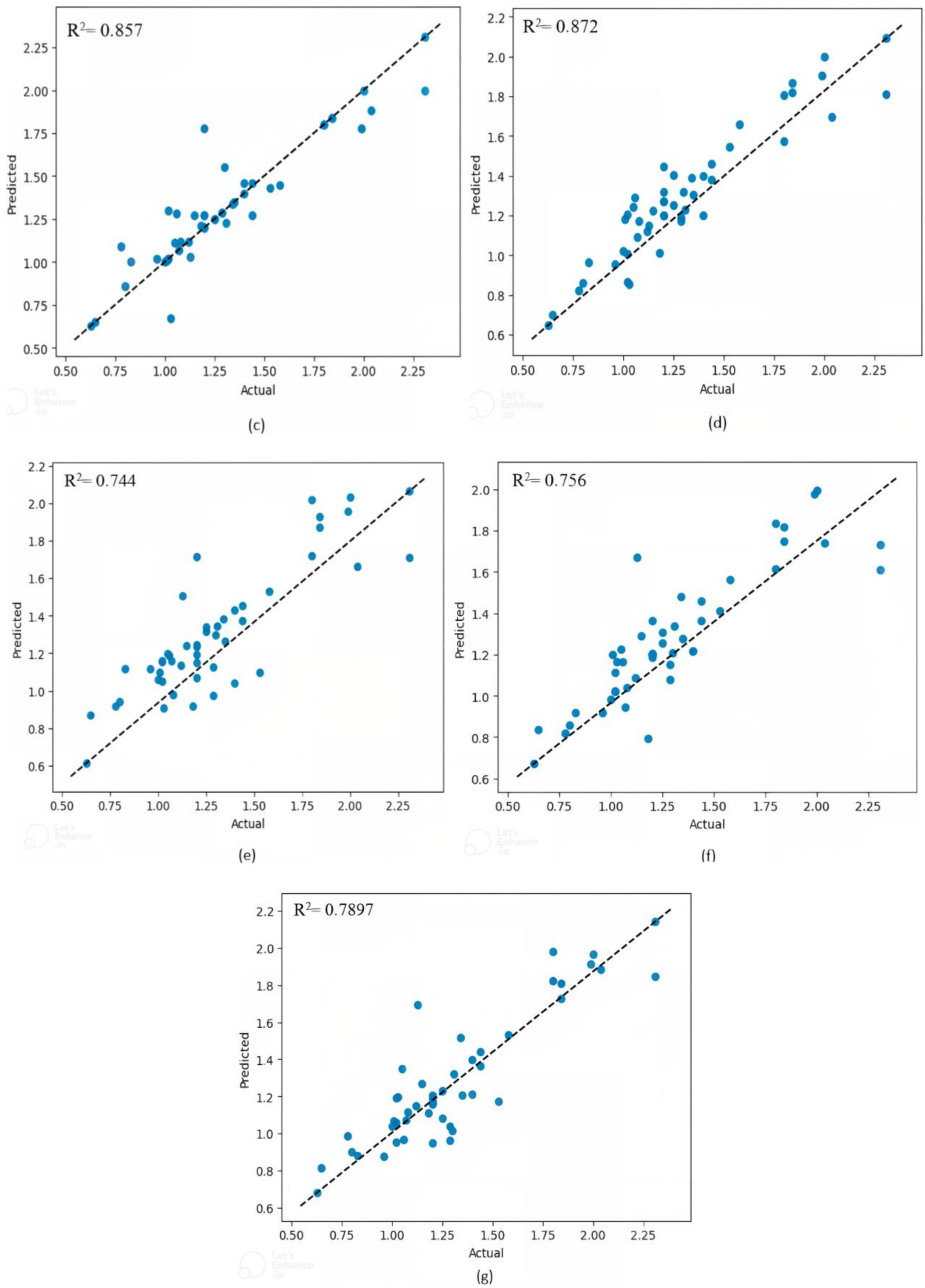



**Figure 4.** Models comparison between predicted and actual FS results based on the testing subset: (a) LR, (b) PR, (c) DT regression, (d) RF regression, (e) SVM regression, (f) KNN regression, and (g) DNN regression

The range of $R^2$ values was between 0.241 (PR model) and 0.875 (RF model), with an average value of 0.651. The bias factor result indicated that the percentage of K values below one varied from 40.81% to 69.38%, with an average value of 51.66%. Therefore, the level of conversation is neutral (without overestimating or underestimating FS) for all regression models, except for the DNN model (%K < 1 = 69.38). The range of RI values was between 0.142 (RF model) and 0.335 (LR model), with an average value of 0.223. The range of RD values was between 0.101 (RF model) and 0.267 (LR and PR models), with an average value of 0.171.

Compared to the seven regression models (LR, PR, DT, RF, SVM, KNN, and DNN), the RF model was the most precise since the $R^2$ value was the highest, at 0.875; %K < 1 was neutral, at 43.47%; and RI and RD values were the lowest, at 0.142 and 0.101, respectively.

Since the RF model performed well, as evidenced by the statistical indices MAE, MSE, RMSE, MAPE, $R^2$, %K < 1, RI, and RD for both training and testing subsets, the model is recommended for estimating the FS for slope stability. Figure 5 displays a comparison between predicted and actual FS results for the RF regression model, with results of training and testing subsets closely aligned along the diagonal axis.

### 3.2. Classification Models

The slope FS was classified into two categories: a stable slope encoded as 1, and an unstable slope encoded as 0. Six classification models, DT, RF, SVM, KNN, DNN, and NB, were developed to classify the FS with hyperparameter results shown in Table 8.

Figure 6 shows the confusion matrix for each FS classification model. The diagonal matrix denotes the instances that were correctly classified, and the off-diagonal matrix denotes the instances that were incorrectly classified. It is noted that the errors, or off-diagonal values, of the DT, RF, SVM, KNN, DNN, and NB classification models were 3, 1, 3, 3, 4, and 10 cases, respectively.

Given the relatively low error rates compared to the total number of cases (49), it is concluded that ML classification models are reliable for classifying the FS of slopes. In particular, the RF classification model performed the best since the error cases were the lowest (1).

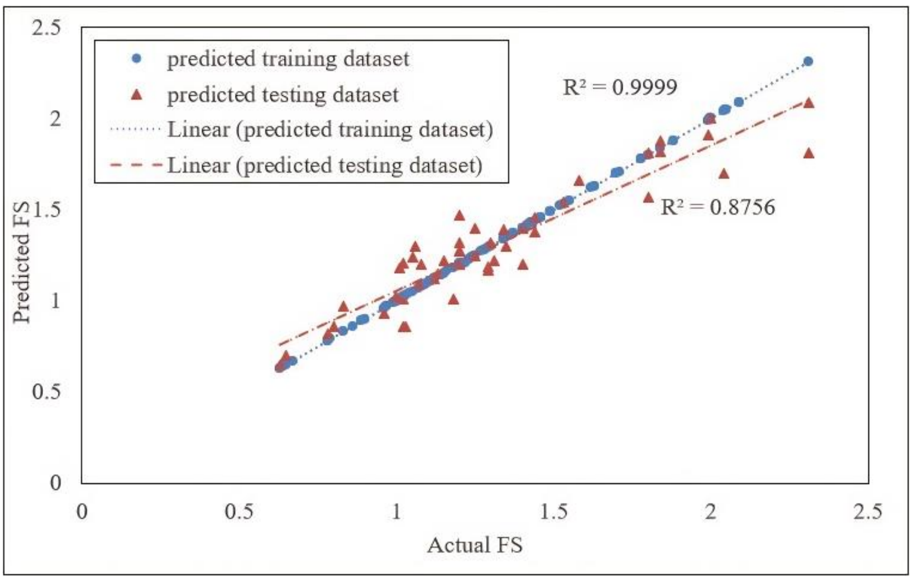



**Figure 5.** Comparison between predicted and actual values of FS for RF regression model based on the training and testing subsets

**Table 8.** Tuning parameters for the classification models

| Classification Model | Hyperparameter |
|---|---|
| Decision tree | CV =5, n_iter = 200, Max. depth = 7, Min. samples leaf = 1, Random state = 42, Criterion = Gini |
| Random forest | CV =3, n_iter = 200, Max. depth = 10, Min. samples leaf = 1, Random state = 80, n_ estimators =20, bootstrap = False |
| Support vector machine | CV =5, n_iter = 100, Kernel = rbf, C= 1.8, random state =42 |
| K-nearest neighbor | n_ neighbors = 3 |
| Deep neural network | # Hidden layer =3, # nodes in each layer = 7, 10, 5, 1, activation function = relu, optimizer algorithm = Adam, epochs =1200, batch size= 108 |
| Naïve Bayes | - |

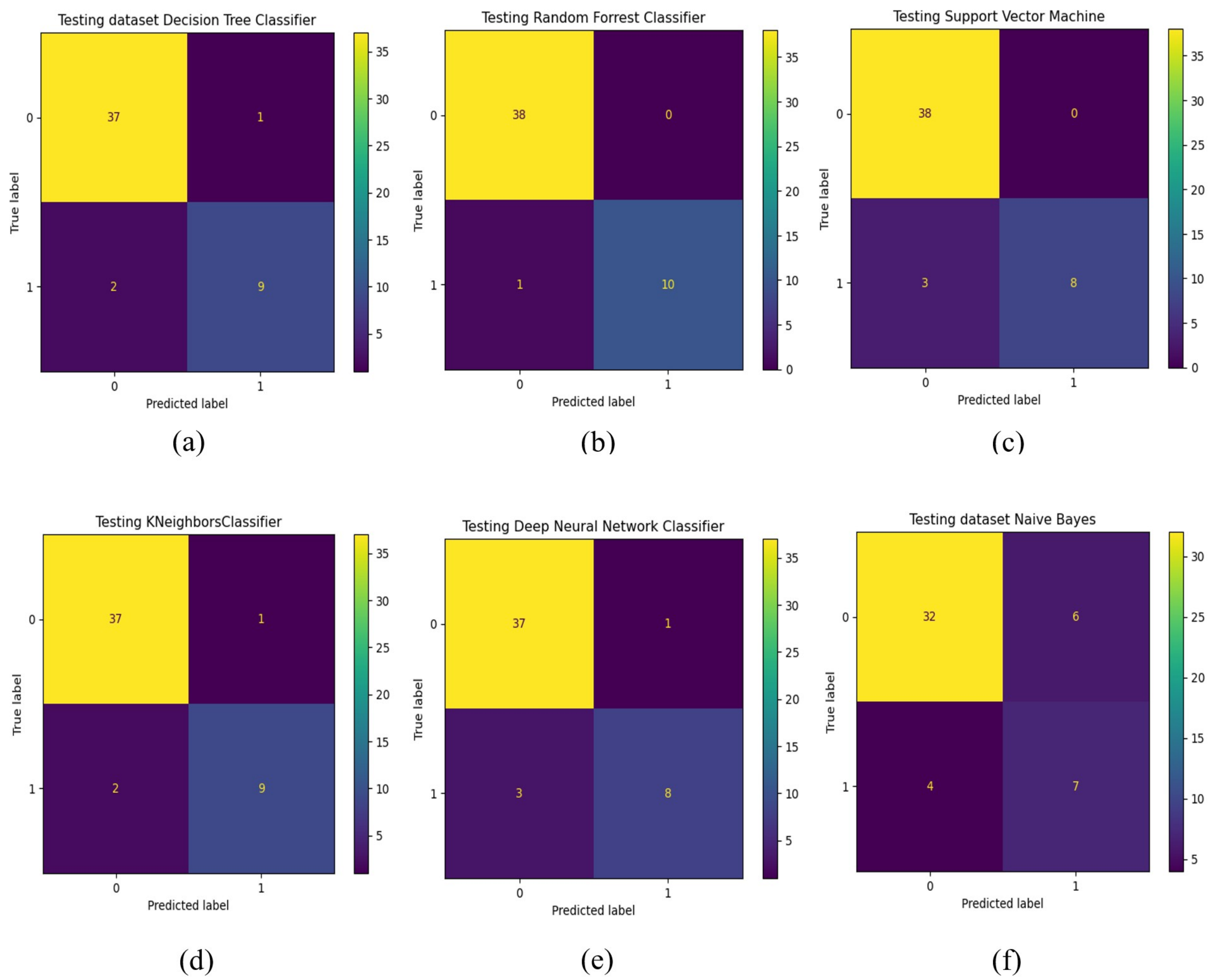



**Figure 6.** Confusion matrix for FS classification models based on the testing subset: (a) DT, (b) RF, (c) SVM, (d) KNN, (e) DNN, and (f) NB

**Table 9.** Performance of the confusion matrix for classification models (Testing subset)

| Model | Parameter | Precision | Recall | F1-score | Accuracy |
|---|---|---|---|---|---|
| Decision tree | Stable | 0.90 | 0.82 | 0.86 | 0.94 |
| | Unstable | 0.95 | 0.97 | 0.96 | |
| Random forest | Stable | 0.99 | 0.91 | 0.95 | 0.98 |
| | Unstable | 0.98 | 0.99 | 0.99 | |
| Support vector machine | Stable | 0.99 | 0.73 | 0.84 | 0.94 |
| | Unstable | 0.93 | 0.99 | 0.96 | |
| K-nearest neighbor | Stable | 0.90 | 0.82 | 0.86 | 0.94 |
| | Unstable | 0.95 | 0.97 | 0.96 | |
| Deep neural network | Stable | 0.89 | 0.73 | 0.80 | 0.92 |
| | Unstable | 0.93 | 0.97 | 0.95 | |
| Naïve Bayes | Stable | 0.54 | 0.64 | 0.58 | 0.80 |
| | Unstable | 0.89 | 0.84 | 0.86 | |

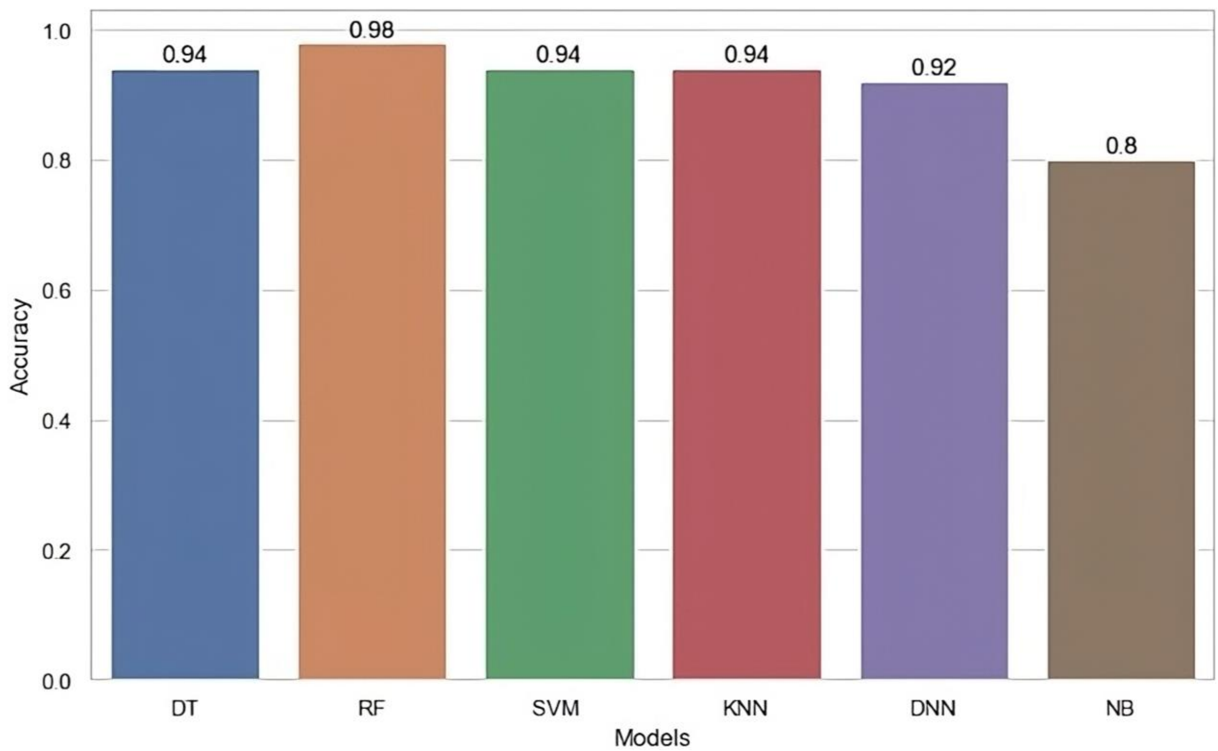



**Figure 7.** Accuracy of machine learning models for FS classification based on the testing subset

Based on the testing subset, Table 9 presents the performance of confusion matrix results for all models. The precision values for the classification models were as follows: DT = 0.90, RF = 0.99, SVM = 0.99, KNN = 0.90, DNN = 0.89, and NB = 0.54. Recall values for each classification model were as follows: DT = 0.82, RF = 0.91, SVM = 0.73, KNN = 0.82, DNN = 0.73, and NB = 0.64. F1-score values for the classification models were DT = 0.86, RF = 0.95, SVM = 0.84, KNN = 0.86, DNN = 0.80, and NB = 0.58. The accuracy values for each classification model were as follows: DT = 0.94, RF = 0.98, SVM = 0.94, KNN = 0.94, DNN = 0.92, and NB = 0.80, as shown in Figure 7.

Since the above indices were high, ML models are recommended as excellent classification tools for reliable stability classification. Specifically, the RF classification model is considered the best as it offered the highest values of precision, recall, F1-score, and accuracy (0.99, 0.91, 0.95, and 0.98).

### 3.3. Sensitivity Analysis

Identifying the most significant and influential input parameters is important. It helps to make informed decisions during the initial planning and design stages of a project. Evaluating the significance of parameters is challenging since 1) correlations can make irrelevant parameters more significant than others, and 2) the assessment criterion strongly influences the order of relative significance of the parameters.

Nevertheless, the impact of the input properties $\gamma$, C, ø, $\beta$, H, and $r_u$ on the FS was assessed through a sensitivity analysis using the RF regression model. The study employed one-way sensitivity analysis, in which a single input parameter was altered sequentially while maintaining all other input parameters unchanged. The reference input values were $\gamma$ = 20.41 kN/m$^3$, C = 24.9 kN/m$^2$, ø = 13$^o$, $\beta$ = 22$^o$, H = 10.67 m, $r_u$ = 0.35, and FS = 1.4. The parameters $\gamma$, C, ø, $\beta$, and H were increased by 10 units, while $r_u$ was increased by 0.1 unit.

As shown in Table 10, sensitivity analysis results indicated that all parameters are relatively important to the FS. The relative significance scores were positive for $\gamma$ (1.29%), C (10.21%), and ø (2.71%), and negative for $\beta$ (-8.00%), H (-1.07%), and $r_u$ (-2.21%). It is evident that the variable C had the highest significance score while slope height had the least impact. Therefore, the most significant and influential parameter is soil cohesion, highlighting the importance of determining the proper shear strength parameters. This finding aligns with Qi and Tang [44] results.

### 3.4. Model Validation

The suggested RF regression model yielded accurate predictions of FS within the model-building dataset, which included both the training and testing subsets. However, understanding its rationale is crucial when evaluating the model's predictive capability in relation to other case studies. Therefore, a validation dataset was constructed using separate, well-documented FS values distinct from those used in the model-building dataset. The validation dataset, as shown in Table 11, consisted of 20 records collected from 13 independent references [45-57]. The statistical distribution of the validation and model-building datasets is similar. Each record in the validation dataset contained six input properties: γ, C, ø, β, H, and $r_u$, and the output parameter FS.

To judge the robustness and credibility of the suggested ML models, the proposed RF model was implemented on the validation dataset. As shown in Table 11, the discrepancy between predicted and actual FS results ranged from 0.12% to 14%, with an average value of 4.9%, which is relatively low.

The RF model's excellent predictive capability is visually demonstrated in Figure 8, where an assessment was made between predicted and actual FS values based on the validation dataset. The $R^2$ value of 0.8736 is considered reasonably high and provided an overall assessment of the model when the validation dataset was utilized.

These findings confirm the RF model's coherence and applicability within the validation dataset, indicating its ability to accurately predict the FS for slope stability as an alternative to classical methods.

**Table 10.** Sensitivity analysis results using the RF regression model

| Property | γ | C | ø | β | H | $r_u$ | FS | Significance score (%) |
|---|---|---|---|---|---|---|---|---|
| Original | 20.41 | 24.9 | 13 | 22 | 10.67 | 0.35 | 1.400 | |
| γ | 30.41 | 24.9 | 13 | 22 | 10.67 | 0.35 | 1.418 | 1.29 |
| C | 20.41 | 34.9 | 13 | 22 | 10.67 | 0.35 | 1.543 | 10.21 |
| ø | 20.41 | 24.9 | 23 | 22 | 10.67 | 0.35 | 1.438 | 2.71 |
| β | 20.41 | 24.9 | 13 | 32 | 10.67 | 0.35 | 1.288 | -8.00 |
| H | 20.41 | 24.9 | 13 | 22 | 20.67 | 0.35 | 1.385 | -1.07 |
| $r_u$ | 20.41 | 24.9 | 13 | 22 | 10.67 | 0.45 | 1.369 | -2.21 |

**Table 11.** Comparison between actual and predicted values of FS with the validation dataset (RF model)

| No. | γ (kN/m$^3$) | C (kN/m$^2$) | ø (degree) | β (degree) | H (m) | $r_u$ | FS (Actual) | FS (Predicted) | Error (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 20 | 10 | 20 | 33.69 | 10 | 0 | 1.320 | 1.420 | 7.58 |
| 2 | 18 | 20 | 20 | 71.6 | 15.2 | 0 | 1.130 | 1.108 | -1.95 |
| 3 | 20.27 | 31.7 | 13 | 26.57 | 10.5 | 0 | 1.640 | 1.642 | 0.12 |
| 4 | 12 | 23 | 25 | 41.01 | 45.5 | 0 | 1.030 | 1.062 | 3.11 |
| 5 | 19.61 | 14.71 | 20 | 20.56 | 30 | 0 | 1.520 | 1.603 | 5.46 |
| 6 | 19.24 | 22.8 | 35 | 33.69 | 12.19 | 0 | 1.780 | 1.852 | 4.04 |
| 7 | 22 | 16.8 | 37.5 | 20 | 44.2 | 0 | 1.370 | 1.342 | -2.04 |
| 8 | 18.71 | 0 | 14 | 26.57 | 13.7 | 0 | 1.290 | 1.209 | -6.28 |
| 9 | 18.5 | 15 | 15 | 45 | 8.2 | 0 | 1.12 | 1.069 | -4.55 |
| 10 | 18.5 | 10 | 15 | 26.57 | 8 | 0 | 1.290 | 1.217 | -5.66 |
| 11 | 19 | 33 | 29.5 | 29.05 | 67.8 | 0 | 1.210 | 1.218 | 0.66 |
| 12 | 18 | 20 | 25 | 56.3 | 22 | 0 | 1.143 | 1.259 | 10.15 |
| 13 | 19 | 25 | 35 | 56.3 | 54 | 0 | 1.239 | 1.140 | -7.99 |
| 14 | 20 | 30 | 35 | 56.3 | 46 | 0 | 1.352 | 1.323 | -2.14 |
| 15 | 22 | 100 | 40 | 63.43 | 115 | 0 | 1.320 | 1.354 | 2.58 |
| 16 | 22 | 70 | 40 | 63.43 | 105 | 0 | 1.345 | 1.382 | 2.75 |
| 17 | 20 | 35 | 30 | 63.43 | 54 | 0 | 1.100 | 1.254 | 14.00 |
| 18 | 18 | 10 | 30 | 45 | 20 | 0 | 1.131 | 1.184 | 4.69 |
| 19 | 19 | 20 | 25 | 63.43 | 23 | 0 | 1.148 | 1.258 | 9.58 |
| 20 | 18 | 3 | 38 | 33.69 | 10 | 0 | 1.537 | 1.590 | 3.45 |

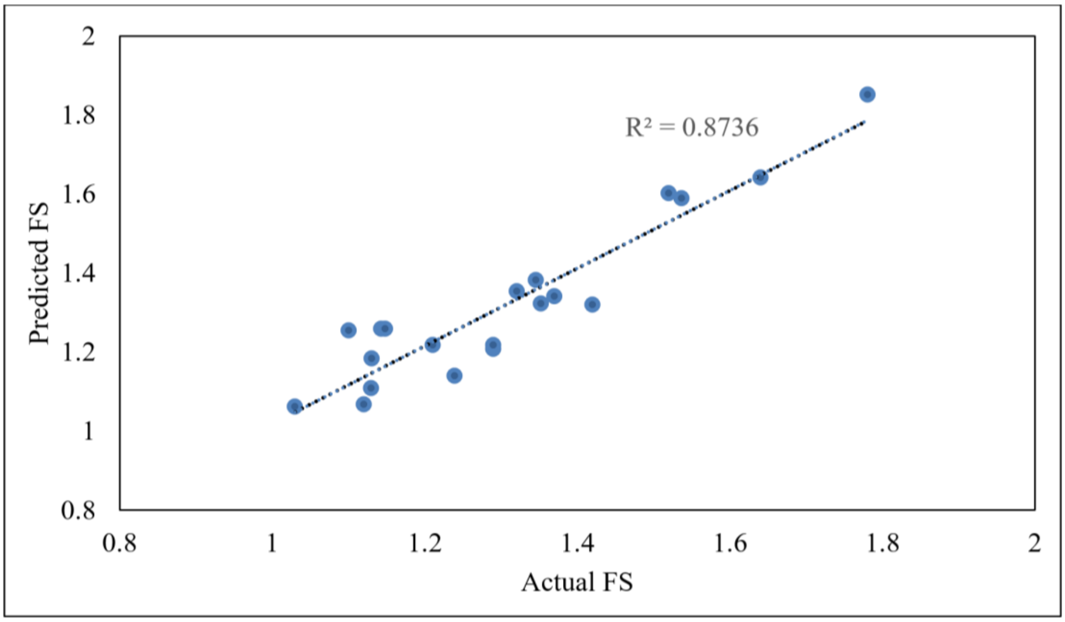



**Figure 8.** Comparison between predicted and actual values of FS with the validation dataset (RF model)

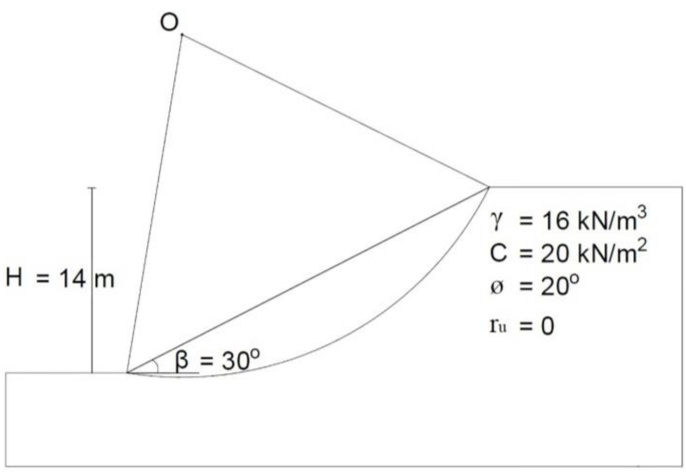



**Figure 9.** Soil and geometric data of the illustrative example

### 3.5. Reliability of the Proposed Model – An Illustrative Example

To show the advantage of the suggested model, the FS of a standard slope is computed using both limit equilibrium methods and the RF model.

As shown in Figure 9, soil properties for the considered slope are C = 20 kN/m$^2$, ø = 20$^o$, γ = 16 kN/m$^3$, while slope geometric properties are β = 30$^o$, H = 14 m, and $r_u$ = 0. Geostudio is utilized to measure the features of the stability analysis based on limit equilibrium procedures. It is a 2D slope stability software used to evaluate the FS and determine the risk of failure with circular/noncircular failure slips within a soil mass. The slope is examined using five traditional methods: Bishop, Fellenius, Janbu, Morgenstern and Price, and Spencer. The modeling is carried out using the developed RF model. A sample stability analysis outcome with the Bishop method is presented in Figure 10.

As shown in Table 12, the FS results obtained from the five limit equilibrium methods were closely aligned with each other (1.576, 1.497, 1.458, 1.573, and 1.573), with an average value of 1.535. Alternatively, the FS obtained from the RF model was 1.461, which was comparatively lower than those obtained from the limit equilibrium methods. This suggests that the limit equilibrium methods may overestimate the slope FS. Furthermore, the resulting error with the five limit equilibrium methods was within a 7% margin, with an average value of 4.829%, and that is within the engineering error criteria. This finding indicates that the suggested model is well-suited for evaluating the safety of slopes.

Since the example result (FS = 1.461) was derived from actual field data, the suggested RF model simplifies FS calculations and can be confidently used in practice as an alternative to sophisticated limit equilibrium techniques.

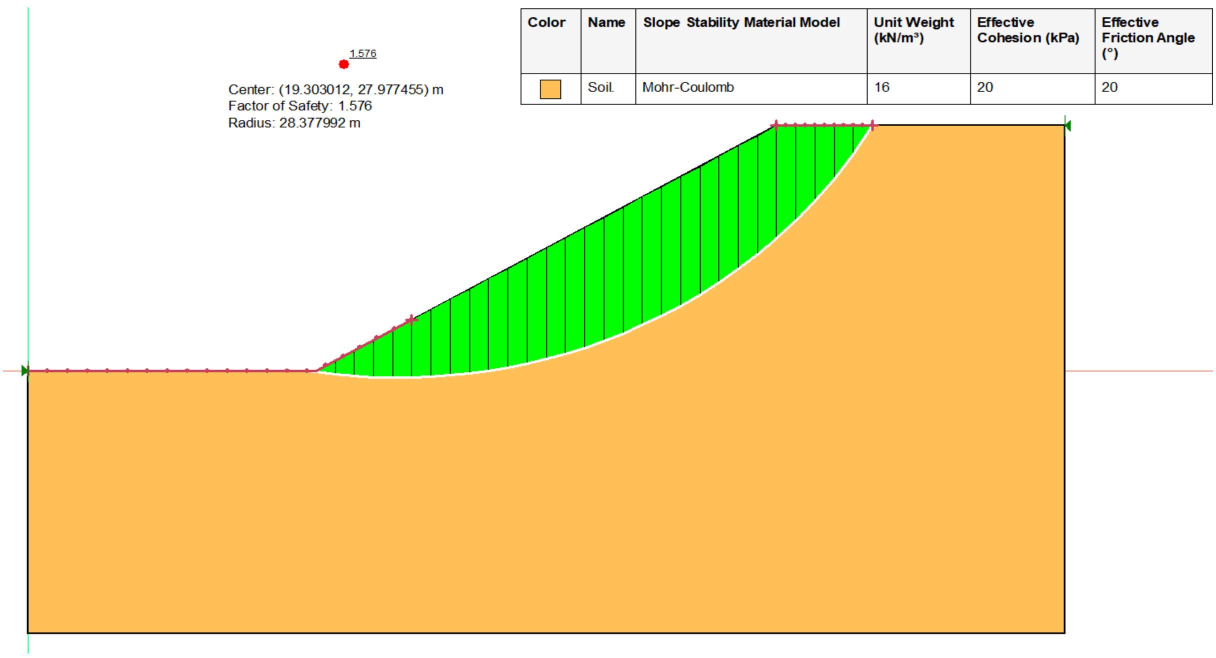



**Figure 10.** Results of slope stability analysis using the Bishop method by Geostudio

**Table 12.** Comparative investigation of the FS calculation results using different methods

| No | Analysis Method | FS | Error (%) |
|---|---|---|---|
| 1 | Bishop | 1.576 | 7.297 |
| 2 | Fellenius | 1.497 | 2.405 |
| 3 | Janbu | 1.458 | 0.206 |
| 4 | Morgenstern and Price | 1.573 | 7.120 |
| 5 | Spencer | 1.573 | 7.120 |
| 6 | Random forest model | 1.461 | - |

## 4. Summary and Conclusions

Given the inevitability and catastrophic effects of slope failure on society, this study aimed to predict and classify the slope FS using classical and ML methods. The predictive capabilities of the proposed models were thoroughly and systematically evaluated. The study recommended a specific valuable model for predicting the FS, based on a wide range of comprehensive and well-established slope cases sourced from reliable literature.

The model-building dataset contained 242 slope cases. For model development, it was split into 193 records (80%) for the training subset and 49 records (20%) for the testing subset. Models were written using Python, which was an excellent tool for developing comparative regression and classification models. The input parameters $\gamma$, C, ø, $\beta$, H, and $r_u$ were employed for model development, with the FS selected as the output parameter. Regression and classification models were assessed using eight statistical indices and the confusion matrix.

The LR and PR models showed poor performance, while ML models DT, RF, SVM, KNN, DNN, and NB demonstrated better feasibility and effectiveness in predicting and classifying slope stability. This success highlighted the credibility of ML algorithms for slope stability assessments compared to classical techniques. Based on the model-building dataset and the unseen independent validation dataset, the RF model was found to exhibit a higher and more reliable prediction of stability state over other ML models, as evidenced by the statistical measures.

Based on the RF model, sensitivity analysis outcomes revealed that the FS for slope stability exhibited an increasing trend in response to increased unit weight, cohesion, and friction angle. Conversely, it showed a decreasing trend with higher slope angle, slope height, and pore water pressure ratio. The most influential parameter was cohesion, since its significance score was maximum (10.21%).

The recommended RF model can be efficiently and accurately used to predict the slope FS as an alternative to classical and sophisticated procedures. The availability of a robust, well-calibrated model helps geotechnical practitioners, planners, and developers make informed planning and design decisions prior to project implementation by enabling quick and accurate estimation of the FS. Such estimation is crucial for the initial assessment of slope failure risk and for selecting the appropriate stabilization techniques. This leads to considerable savings in resource allocation, time, and effort, promoting sustainability in civil engineering and enhancing the safety of projects in collapse-prone terrains.

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## Notation

| | |
|---|---|
| ANN | Artificial neural network |
| BPNN | Back-propagation neural network |
| C | Cohesion |
| CNN | Chaotic neural network |
| DNN | Deep neural network |
| DT | Decision tree |
| ELM | Extreme learning machine |
| FEM | Finite element method |
| FS | Factor of safety |
| $FS_a$ | Actual factor of safety |
| $FS_p$ | Predicted factor of safety |
| H | Height of slope |
| K | Bias factor |
| KNN | K-nearest neighbor |
| LEM | Limit equilibrium method |
| LR | Linear regression |
| MAE | Mean absolute error |
| MAPE | Mean absolute percentage error |
| ML | Machine learning |
| MSE | Mean square error |
| NB | Na ïve Bayes |
| NBC | Na ïve Bayes classifier |
| PR | Polynomial regression |
| PSO | Particle swarm optimization |
| $R^2$ | Coefficient of determination |
| RD | Ranking distance |
| RF | Random forest |
| RI | Ranking index |
| RMSE | Root mean square error |
| $r_u$ | Pore water pressure ratio |
| SVM | Support vector machine |
| ø | Friction angle |
| β | Slope angle |
| γ | Unit weight |

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