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Application of Machine Learning Models for Slope Instabilities Prediction in Open Cast mines

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Abstract: Because slope breakdown can result in severe disasters, slope stability analysis and prediction are crucial. The effectiveness of four machine learning techniques for the prediction of slope stability was compared in this paper. Conventional analysis of slope instability methods (e.g., originally developed in the early part of the 20th century) were widely employed as design aids. Many academics are drawn to them because they provide more advanced design tools, such as machine learning-based learning analytics. The current study's major goal is to analyze and optimize several ML-based models for predicting the safety factor. We used multiple ML-based techniques in this study to predict the factor of safety against slope instabilities. For slope stability prediction, four regression approaches were used: Support Vector Regression (SVR), Multi-Layer Perceptron (MLP), Multiple Linear Regression (MLR), and Simple Linear Regression (SLR), and. To train and test the four classification techniques, a data set consisting of more than 20 local and international slopes of projects was collected, with essential parameters of the four models tuned using the 5-fold cross validation approach. The four regression algorithms' prediction results were compared and examined. The correctness, Kappa, and receiver operating parametric curve findings show that both of the MLP and MLR models can produce reasonably satisfactory outcomes, with the MLP model outperforming the other three learning approaches.

Keywords: *machine learning; slope failure; 5-fold cross validation, ROC curves.*

1. Introduction

Due to the possible harm that a changing slope might provide to the workforce or the business, observing slope stability (SS) is a crucial necessity in the arena of geosciences. For miners and civil engineering professionals who work with man-made slopes like open-pit walls, dams, embankments of roads and railroads, and hills, slope stability is a critical problem. Creep theory is employed in the construction of rock slopes since the causes of instability are frequently complicated. The forecast of the time of slope failure is difficult due to the complexity of the reasons of slope movement. Engineers have recently been able to better anticipate the effects of slope failures in open-pit mines because to the use of contemporary monitoring systems [1].

There have been several attempts to create a technique that can foretell when something will fail. It is difficult to correctly anticipate the period of slope collapse because factors impacting that is impossible to continually assess slope instabilities due to factors including the environment, physical and geomorphological processes, and human activity [2]. Therefore, practitioners have relied on a thorough examination of slope deformation rather than creating a phenomenological model of slope failure [3].

Geotechnical and Mining applications, such as mechanical property [4]–[6], landslide displacement [7]–[10], rock ruptures [11]–[14], open cast hanging wall [15], [16], and the strength of infill [17], have incorporated different methods for mining data and sophisticated assessment models in recent years. With the increased accessibility of slope characteristics, several learning algorithms have been applied effectively for SS prediction and have shown impressive results. As illustrated in [18], the author's proposal is to evaluate the wide-ranging stability of complex rocky slopes using a cloud method in hilly regions was successful in demonstrating that the cloud method is a workable and trustworthy method for evaluating the wide-ranging stability of rocky slopes. In order to create a regression paradigm for estimating the slope occurrences' safety factor, in [19], author used an approach of genetic algorithm. They discovered that it is an effective and user-friendly method for determining the factor of safety (FoS) for slopes. Sung employed the first and second-order reliability techniques, as well as the Monte Carlo methodology, to determine the chance of slope failure using an ANN model (which has been trained) [20]. In

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order to choose the suitable parameters for an SVM model, in [21], author developed and incorporated the particle swarm optimization (PSO) technique for their research work. The outcomes demonstrated that the combined SVM and PSO model is an effective computational method for predicting SS. Both in [22] and [23] successfully forecast the SS using SVR. For the SS prediction in RF model's training data set, Zhang and Wen

gathered data from 30 examples for the analysis of different models for the effective prediction of dataset. The effectiveness of the trained prediction models was then evaluated using the additional 12 sets of data. They discovered that the model's training is beneficial [24]. A gravitational search algorithm (GSA) was effectively used by the authors in [25] and also the work done by authors in [26] describes to tackle global optimization issues and minimise the safety factor in SS analysis. The forecast outcomes were the same as the actual circumstances after training the Bayes model for prediction with gathered the slope examples and then using it to actual engineering. With strong classification presentation, high forecast accuracy, and a low mis discrimination ratio, this model might be utilized to investigate slope stability is discovered in [27]. Although the aforementioned sophisticated models can all aid in our understanding of slope failures, they are not adequate to provide a comprehensive solution. There hasn't been an evaluation of smart models in their assessment of SS, thus a particular strategy may be advantageous in certain situations but insufficiently successful in others [28], [29]. In the meanwhile, the validation of the dataset by using the cross-validation (CV) technique is an efficient and trustworthy approach to authenticate the generalizability of the model [30], [31], [32], [33], therefore this is required to offer CV for evaluation with routine validation of improved methods.

This research looks at the use of machine learning (ML) to provide reliable predictions. In 1997, Mitchell gave a definition of machine learning as the research into how to create computer algorithms that become better at a task over time [34]. Using algorithms, machine learning enables the computer to examine the data, find patterns, and generate predictions based on the input data. Today, a wide variety of algorithms are available to filter through data, discover apparent and unseen patterns, and apply the discovered pattern to improve judgments. There are 3 primary forms of machine learning, namely, supervised, unsupervised, and semi-supervised learning. Below is a quick explanation of each of the three forms of machine learning:

(i)When learning under supervision has the input consists of a set of data with a known solution; this set of data is referred to as training data. The computer is trained to understand trends and create a model to make accurate predictions using the training data. The model is adjusted for the training phase until the desired results are obtained. Examples of supervised learning are classification and regression [35].

(ii) Unsupervised learning uses a collection of data with an unidentified answer as its input. In unsupervised learning, a model is created by looking for redundancy or similarity in the data, supposing that the incoming data has structures [35].

(iii) Semi-supervised learning uses a blend of known and undiscovered answers in the dataset. The model is created for this learning with the purpose of understanding structure and making predictions [35].

Six relative slope stability characteristics are employed in this work to create intelligent models. In order to assess the slope stability with the parameters, we constructed five traditional soft computing algorithms based on 80% of the 330 examples, incorporating the SVR, MLR, SLR, and MLP. The prediction accuracy of the models is then evaluated using the remaining 20 percent of the instances taken as test samples. The statistical analysis of three metrics is used to describe and for the comparison of the evaluation accuracy parameters of MLP, SLR, MLR and SVR. The sensitivity of attributes are then examined.

The outline of the paper is organised with an introduction followed by methodology and materials in section 2. The section 3 describes the results and discussion. The section 4 ends with concluding remarks with a feature aspect of this research work.

2. Methodology and materials

2.1. Analysis of Parameters

Three parameter-choosing guidelines must be followed in order to prevent overtraining the model. The first rule is that the discriminant indicators should indicate slope stability features through sensitive and stable parameters. The parameters should then be separated from one another physically. The parameter data should also be accessible or simple to collect. Six related parameters are chosen based on the aforementioned analysis. These 6 variables are the weight unit (ω), cohesiveness (c), angle of internal friction (ϕ), slope inclinations (ɨ), the height of slope (ʜ), and pore water ratio (δ). The 3 indices of parameters such as the ω, c, and ϕ can be used for reflecting the mechanical and physical aspects of materials for the analysis of geological slope characteristics. The parameters ɨ and the ʜ represent the organizational features of slopes. The δ represents what causes slope failures to occur outside.

2.2. Slope Data Set

330 various examined phases of intended soil slope were done in the Geo5 program and the FoS achieved for each

matching input condition was taken as output, in order to generate the necessary dataset with regard to the given variables. Following, the MLP, SLR, SVR, and MLR models were trained using 80% of the whole dataset. The remaining 20% was utilised to evaluate the effectiveness of the models. It should be noted that many statistical indicators were used to determine the correlation and inaccuracy between the real and anticipated safety factor. Table 1 displays the statistical characteristics (Max, Min, Mean, and Standard Deviation) of the condensed data set.

TABLE 1. The Slope Samples' Statistical Features.

Parameters	unit weight (ω) in (kN/m3)	cohesiveness (c) in (kPa)	internal friction angle (ϕ) in degree	slope inclination (ɨ) in degree	slope height (ʜ) in (m)	pore water ratio (δ)
Max	31.5	33.5	46	54	395	0.8
Min	15	0	0	18	3.8	0
Mean	20.3	12.65	26.95	34.15	55.19	0.5
Standard Deviation	4.05	14.25	11.35	10.11	72.65	0.57

2.3. Discrimination Methods

The primary goal of this work is to compare and evaluate the effectiveness of many supervised learning methods for the prediction and analysis of SS. According to this, the MLP, SLR, SVR, and MLR machine learning algorithms were taken into account in this study. The four models are intriguing for the current investigation since they have certain traits in common:

- They are becoming more popular due to the their increasing use;
- Some of them having been successfully applied to slope stability prediction tasks;
- Their efficient implementations;
- Their strict mathematical theory foundation;
- Their use of various classifiers to lessen the uncertainty of the results that might be related to the algorithm that each classifier uses; and
- Their reputation for enabling the analysis of the more complex form of nonlinear associations.
-

2.3.1. Multi-Linear Regression

Establishing a linear formula for the sample data in order to show the links between two or more explanatory and response variables is the main objective of the MLR model. It describes the evaluation properties of different responsive variables that are used in the formula. Equation illustrates the general structure of the MLR formula (1) [36]:

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_s x_s + \varepsilon \quad (1)$$

In the equations above, the parameters x and the parameter y represent the value of independent and dependent variables, respectively. MLR unknown parameters are indicated by the words $\alpha_0, \alpha_1, . . \alpha_s$, etc. In the general MLR formula, the normally distributed random variable is also represented by the symbol.

The primary goal of the MLR approach is to approximate the applied unknown components of Equation (i.e., $\alpha_0, \alpha_1, ... \alpha_s$) (1). The practical version of the statistical regression approach is provided by [36] after using the least-squares method:

$$y = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_s x_s + \mathrm{e} \quad (2)$$

where the approximate regression coefficients for 0 and 1, respectively, are represented by $a_0, a_1, . . . a_s$. Term e also denotes the sample's estimated error. The estimate of y is as follows, assuming that term e represents the difference between actual and expected y:

$$y = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_s x_s \quad (3)$$

2.3.2. Multi-Layer Perceptron

Since its introduction by [37], artificial neural networks (ANNs) have been able to provide forecasting tools that resemble biological neural networks. A popular variant of ANN, the multi-layer perceptron (MLP), has demonstrated satisfactory performance in a variety of engineering simulations [38–42]. They are capable of producing the non-linear equations reside between the set of input samples and output values, which is why [43, 44].

The general construction of MLP is shown in Figure 1. Three layers with computational nodes make up a basic MLP neural network (mostly known as neurons).

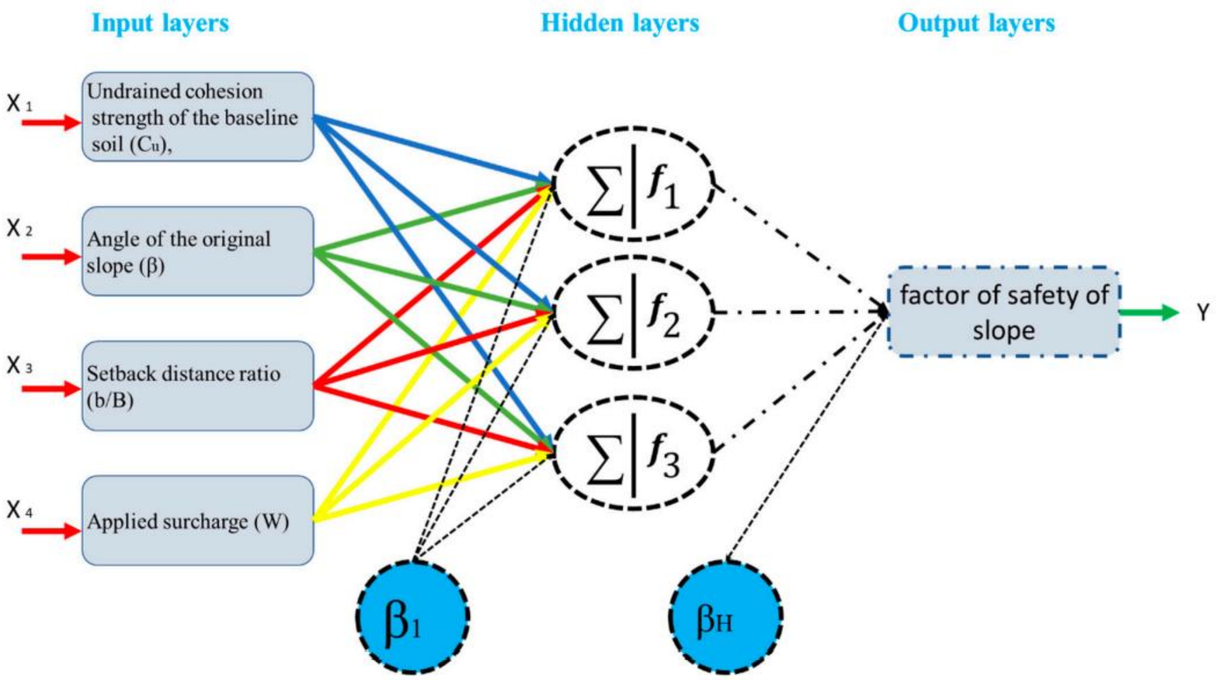

Fig. 1. Multi-layer perceptron (MLP) neural network typical architecture.

The nodes in the input layer receive the first data. In the subsequent steps, the hidden and unseen neurons (i.e., the available neurons in the hidden layer of the model) assign and modify the MLP weights and biases in an effort to determine the link between the inputs and the related targets. Afterward, the neurons operating in the last layer provide the output (i.e., output layer). Consider the S and W to be the input and weight vectors, respectively. The function of each neuron is then expressed as follows:

$$U = \sum_{i=1}^{j}\left(S_i W_{1,i} + b\right) \quad (4)$$

$$Output = F(U) \quad (5)$$

where b is the bias and j represents the number of neurons. Additionally, $F(x)$ denotes the activation function (AF). Keep in mind that this study takes into consideration the feed-forward back-propagation (FFBP) approach, which seeks to reduce the error rate of performance by modifying the MLP model parameters (i.e., biases and weights as parameters). The FFBP approach is extensively covered in previous publications [45].

2.3.3. The Simple Linear Regression (SLR)

SLR primary goal is to determine how a predictor variable affects a certain result. The link between the input sample and target samples is defined by a linear dependence in the suggested method, as the name suggests. Equation (6) may be used to illustrate a simple linear regression formulation in general.

$$y = \alpha + \beta x + \kappa \quad (6)$$

The words and denote the structural parameters, where x and y, respectively, are the independent and dependent variables (intercepts on the y-axis and the slope parameter of the regression line equation, respectively). Additionally, which is expected to be no correlated with a mean of zero and constant variance, defines the random error. Furthermore, studies are frequently related with the assumption of the normal distribution of errors in order to get a greater competency in prediction [46]. Be aware that a transformation procedure can be used to normalise data to the required level [47]. Considering a population of sample sets like $S = \{(x_i, y_i)|i = 1,2, \dots \mathrm{N}\}$, the SLR technique approximates the structural characteristics by using the ordinary least square (OSL) approach (i.e., α and β). Although a normal distribution is not required, it does increase the accuracy of the regression model [48]. In light of this, the created regression model seeks to determine its parameters in a way that yields the lowest possible sum of squared error, or the difference between real value and estimated data sets[49]. Finally, the fitted output (y_i) at each given value of x may be determined after finding the correct values of (intercept) and (slope regression parameter) (x_i).

2.3.4. Support Vector Regression (SVR)

One of the popular machine learning techniques, SVM, seeks to identify the decision boundary that divides several classes. SVR is a popular form of SVM. SVRs are mostly used to tackle difficult regression issues, as their name suggests. Each set of input-target pairings is thought to have a distinct association during SVR learning. The system outputs, such as the slope safety factor in our study, will be produced by grouping and categorising the relationships between these predictors [50]. Instead of minimising computed error, which is the difference between the goal and system outputs, as is the case with many predictive models, SVR tries to enhance its performance by modifying and improving the generalisation boundaries for a regression. A ε-insensitive loss function (LF) can disregard a specified error value in this case [51]. The SVR model incorporating the specified LF (i.e., ε-SVR) seeks for the optimal hyperplane that has the smallest distance from all sample points if we suppose that the training dataset is made up of N pairs of samples, represented by $S = \{ (x_i , y_i) | i = 1,2, \dots \mathrm{N} \},$. In further detail, ε -SVR looks for a function $g(x)$ with the biggest y_i [52] divergence from the target values. As previously stated, ε-LF is used to execute linear regression in high dimensional feature space. Additionally, the less sophisticated the model, the lower the value for $\|w\|^2$ [53]. For the non-linear issues, a kernel mapping function, denoted by γ (x_i), is used to convert the input data into high-dimensional space (x_i). Then, a convex optimization problem is used to apply a linear technique to data in the future space [54, 55].

$$Minimize\ \frac{1}{2}\|w\|^2 + C\ \sum_{i=1}^{z} \Phi_i + \Phi_i{}^* \quad (7)$$

$$subject\ to \begin{cases} y_i - w.\gamma\,(x_i) - b \leq \varepsilon + \Phi_i \\ w.\gamma\,(x_i) + b - y_i \leq \varepsilon + \Phi_i{}^* \\ \Phi_i, \Phi_i{}^* \geq 0 \end{cases} \quad (8)$$

where, respectively, the words w and C stand for the weight vector and penalty parameter. Additionally, the parameters Φ_i and $\Phi_i{}^*$ represent the slack variables measuring the abnormality of trained data beyond the ε-LF zone, and b determines the bias. In the formula above [56], the accuracy factor is also indicated by the symbol. In other words, the error function ε [57] will only take into account samples having a deviation value greater than. After inserting the Lagrange multipliers of $\rho_i\ and\ \rho_i{}^*$, a linear combination is built to calculate the SVR results:

$$f(x_i) = w.\gamma(x_i) + b = \sum_{i=1}^{z}(\rho_i - \rho_i{}^*)\gamma(x_i).\gamma\,(x) + b) \quad (9)$$

2.3.5. Validation Method of the proposed models

To improve the generalization power of the suggested models, all four models feature hyper-parameters (referred to as essential factors in this study). There are other techniques, such as the simple conventional method, the holdout method, the bootstrap method, and the bolstered method [39]. K-fold cross validation is one of these techniques, and it is perhaps the most popular (CV). The k-fold CV approach is often thought to produce a model with superior generalization capabilities. Thus, during the hyper-parameter tuning, the 5-fold CV approach (5 being the number of folding options advocated by Kohavi [59]) was utilized to elevate the generalization capacity of this model in this research. The training dataset is randomly divided into five folds in this approach [21], [38], [60]. Four of them are utilized as a training subset to construct models, while the remaining one is used as a validation data to validate the performance of the models. The method will be repeated five times with a new fold serving as the confirming fold each time. Averaging the results of five iterations yields the overall effectiveness of the prediction models on the training dataset. This approach was utilized for parameter assortment and for the avoidance of model overfitting. The test set of model was never used throughout the process to construct models, but it was applied for the testing of the forecasting ability of the concluding method.

2.4. Flow chart

Based on the above parametric descriptions the overall flowchart of the study consist of the following few lines. Initially the dataset collected from the software and divided into train and test data sets and also few set of validation datasets. Then by the application of 5 fold cross validation techniques, different machine learning applications were conducted and a comparison study is conducted with the models.

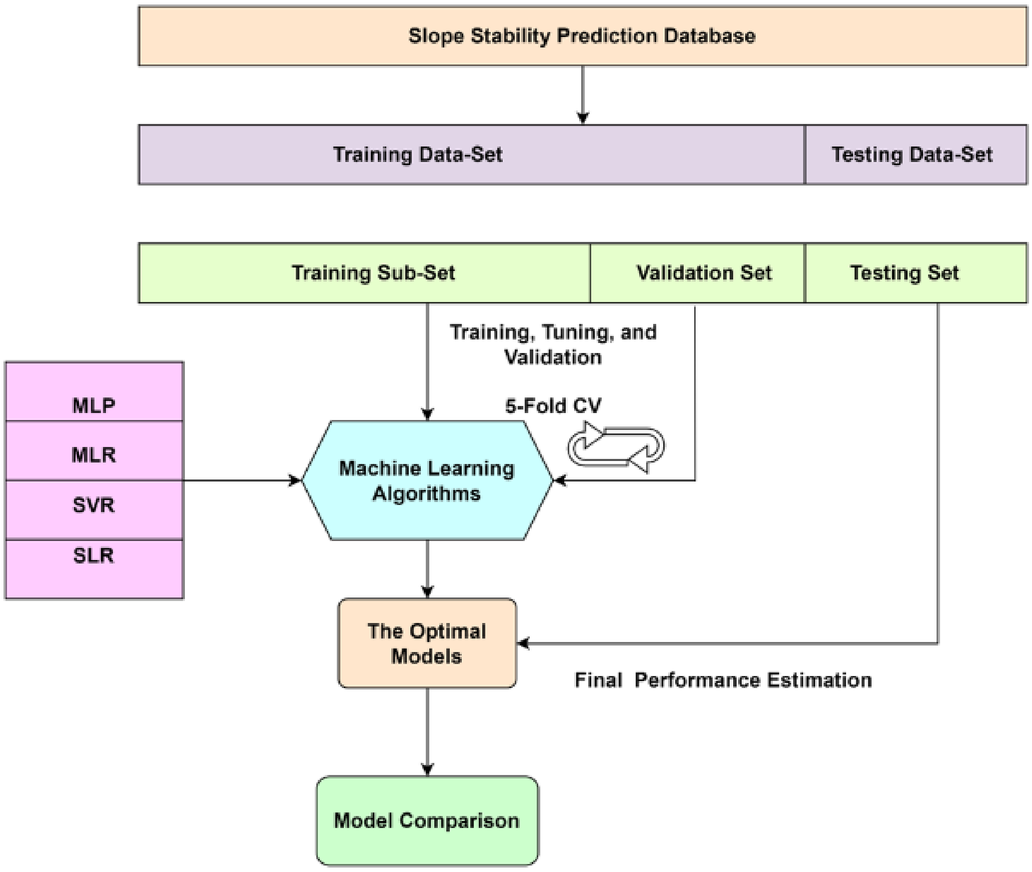

Fig. 2. Flow Chart of the Proposed Methodology

2.5. Discrimination Performance

There isn't a standard way to evaluate categorization model performance. Three measures (Kappa, accuracy, and AUC which is the used area under the ROC curve) are used to assess the prediction act of ML systems, according to prior study findings [21], [37]-[39], [51]-[55]. The three metrics must be calculated using a confusion matrix. One of the fundamental instruments for assessing the confidence in various algorithms is the confusion matrix. Given that the slope stability analysis is a two-class problem in the revision process, the confusion matrix is a 2X2 matrix. The confusion matrix appears as follows:

$$M = \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \end{bmatrix} \quad (10)$$

where x_{11} and x_{22} are the number of properly predicted samples, x_{11} is the number of class 1 samples, x_{22} is the number of class 2 samples, x_{12} is the number of class 1 samples correctly anticipated to go into class 2, and x_{21} is the number of class 2 samples correctly projected to go into class 1. Class 1 in this study indicates a steady slope, whereas class 2 indicates failure.

The accuracy may be determined using Eq. 11, and the accuracy can be used to evaluate the discriminant abilities of the four models. When coding categorical variables, Cohen's Kappa is the index used to assess inter-rater reliability. In comparison to using percentages to assess dependability, this statistic is thought to be more reliable [54, 56]. Eq. 12 can be used to administer the Kappa.

$$Accuracy = \left(\frac{1}{n} \sum_{i=1}^{m} x_{ii}\right) \times 100\% \quad (11)$$

$$Kappa = \frac{n \sum_{i=1}^{m} x_{ii} - \sum_{i=1}^{m} (x_{i+} \cdot x_{+i})}{n^2 - \sum_{i=1}^{m} (x_{i+} \cdot x_{+i})} \quad (12)$$

x_{i+} are the no. of data samples that belong to class I and $x_{+i}$are the no. of samples that are projected to class j. Where n the total number of instances in the data set is, m is the number of types of slope stability factor, and m is 2 in this research. Kappa values fall between -1 and 1, and they may be categorised into six groups of parameter level to indicate various degrees of constancy (as shown in Table 2). According to general rules, the strength of agreement is bad if the Kappa value is less than 0.4 and high if it is greater than or equal to 0.4 [57].

Table 2. Description Kappa Scale Value

Agreement Strength	Kappa
Total factor of Disagreement	[-1.0, 0.0]
Slightly	[0.0, 0.2]
Poorly	[0.2, 0.4]
Moderately	[0.4, 0.6]
Substaintially	[0.6, 0.8]
Perfectly	[0.8, 1.0]

The truly predicted positives and falsely predicted positives cases are represented graphically by the ROC curve [58-61]. Based on the ROC curve's shape and area under it, one may evaluate the effectiveness of various methods (AUC). The ROC curvatures for each of the method may be strained into a single graph to compare the performance of the discriminant algorithms graphically. The method would be useful to use the ROC curve in the upper-left corner. The most accurate findings and has a higher discriminant performance. The AUC of each ROC curve may also be used to compare the performance of various methods, and Table 3 displays the classification results for the AUC value [55]. The ROC curvature method with the highest AUC exhibits the greatest level of discriminant. The performance of radar was initially assessed using the ROC curve. The approach is used in this work to assess and contrast the discriminant level of performance of MLP, SLR, SVM, and MLR models for forecasting SS.

Table 3. Scale of AUC Value

Level	AUC value
Excellent	(0.91,1.0]
Good	(0.81, 0.9]
Moderate	(0.7,0.8]
Poor	(0.61,0.7]
Bad	(0.61, 0.5]

3. Results and Discussion

Table 4 describes the testing and training results of SS found in the four methods. Sample numbers that are accurately anticipated are represented by the values in true columns, whilst inaccurately predicted sample numbers are represented by the values in false columns. According to the outcomes in Table 4, the MLP approach is capable of producing good results for the testing set. The MLR model can also produce good results, with 30 instances being genuinely predicted, even if the available numbers of samples sets in true columns of testing samples are fewer than those of the MLP method (32 cases being truly predicted). As a result, when compared to other approaches, both the MLP and MLR models have more discriminant power for slope stability, and the MLP model performs more completely than the other three models.

Table 4. Prediction results of different models for testing dataset

Types	MLR		SVR		SLR		MLP	
	True	False	True	False	True	False	True	False
Stability (18)	16	2	8	10	6	12	16	2
Failures (18)	14	4	16	2	14	4	16	2

3.1. Comparison of the four models

Table 5 displays the Kappa and accuracy values for each model for the testing set. As can be observed, the four models' accuracy ranges from 0.5756 to 0.9089, with the MLP model having the greatest accuracy rate (90.89%), followed by the SVR, MLR, and Bayes models, which have accuracy rates of 85.33%, 68.67%, and 57.56%, respectively. The Kappa values of the MLR, SVR, SLR, and MLP models, on the other hand, fell between [0.122-0.799]. Only the Kappa values of MLR and MLP are higher than 0.39, and the agreement strength of Kappa ranges from minor to large. The Kappa of the MLP is clearly the highest with a value of 0.78, followed by the SLR, MLR, and SVR models, as shown in Table 5. Over testing samples, MLP has a better capacity to generalise. In other words, the MLP model is practical and useful for forecasting SS.

Table 5. Metrics values of different models

Data Set	Metrics	MLR	SVR	SLR	MLP
Testing Dataset	Accuracy	85.33%	68.67%	57.56%	90.89%
	Kappa	0.678	0.339	0.122	0.799

The 4 methods' ROC curves for the test set are shown in Fig. 5. The algorithms that correlate to the four ROC curves are Bayes, SVM, RF, and GSA models sequentially in the set, according to comparisons of the ROC curve shapes.

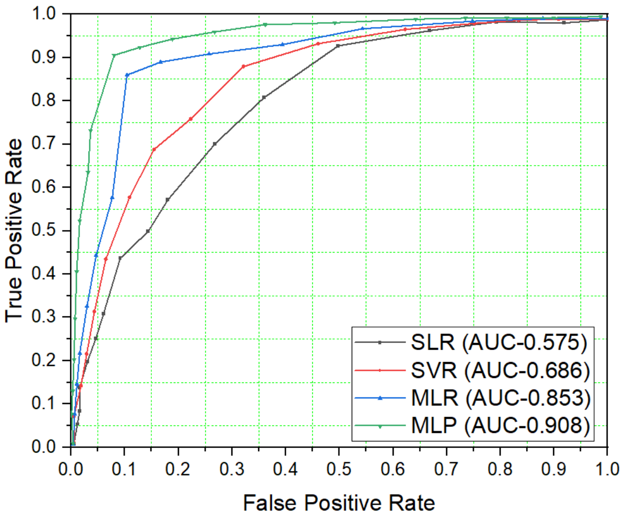

Fig. 5. Comparative ROC Curve

The SS prediction AUCs of the four discriminators vary from [0.575-0.908], with the MLP model obtaining the greatest AUC with an AUC of 0.908, followed by the MLR technique (AUC = 0.853), SVR, and SLR models. Thus, for each type of slope stability, the MLP and MLR models may produce results that are adequate, and the MLP technique performs better than the MLR, SVR, and SLR methods. This study examines the performance and application of the MLR, SVR, SLR, and MLP models for slope stability. Both MLP and MLR may provide respectably excellent discriminating outcomes, as seen by the accuracy parameter, Kappa values, and ROC curvatures of each of the model, but here the MLP model out performs and it gives an overall better result.

4. Conclusions

Approaches for determining slope stability could be useful in real-world applications. MLR, SVR, SLR, and MLP approaches are used to distinguish slope stability in this study. Six parameters (ω, c, ϕ, ɨ, μ, and δ) are evaluated, and 330 slope instances collected through the simulation software are used to build the four models. The following are the conclusions.

(1) Among the four algorithms, the MLP and MLR outperform the SVR and SLR in slope stability prediction. The MLP has an accuracy parameter, Kappa value, and AUC of 90.89%, 0.799, and 0.908, which are considered to be excellent predictions result.

(2) All of the study's parameters are vulnerable to slope failure, therefore determining slope stability using a single metric is useless. The variable δ is perhaps the most profound aspect to MLR model and MLP models, while slope geometry attributes are also critical. It should also be highlighted that neither of the supervised learning techniques are suitable for all kinds of slope scenarios, and none were sufficiently to address the existing problem.

Author contributions

All authors have equally contributed for this research work.

Conflicts of interest

The authors declare no conflicts of interest.

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