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Machine Learning Based Unified Framework for Slope Stability Prediction

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Abstract

The major objective of this research is to evaluate and enhance nine machine learning (ML)-based techniques for establishing slope safety parameters. Various algorithms are employed during the development of ML models, including multiple linear regression (MLR), artificial neural network (ANN), gradient boosting classifier (GBC), support vector classification (SVC), logistic regression (LR) classifier, Naive Bayes (NB) classifier, decision tree (DT) classifier, and random forest (RF) classifier. In-depth data-sets are prepared for the use of artificial intelligence techniques using well-known limit equilibrium-based slope stability techniques such as Fellenius, Bishop's, Janbu, Morgenstern-Price, and Spencer's approaches. A total of 4208 data-sets, including 3366 training and 842 testing data-sets with varying geometric properties of slope and soil properties are used to train the prediction model. Statistical indicators like the coefficient of determination (R^2), mean absolute error (MAE), accuracy, precision, recall, and F-1 score are used to evaluate the effectiveness of the predictive model. The DT, ANN, and SVC models of classification outperform other classification models according to the score awarded to each model based on their ranking in performance metrics, with their total scores of 25, 21, and 20 respectively. With coefficients of regression of 0.966 and 0.973 for training and testing datasets, respectively, Spencer's approach to the ANN model predicts most accurately for both training and testing datasets. In all circumstances of regression algorithms, the prediction performance of the ANN model built for all approaches outperforms that of the MLR model. The equation for prediction from MLR can be used in slope stability problems for similar slopes in future.

Keywords

Slope Stability, Machine Learning, Factor of Safety, Limit Equilibrium Analysis

1. Introduction

The safety and sustainability of several engineering projects, including highways, railway embankments, dams, cut slopes, natural slopes, and retaining walls, are significantly impacted by the stability of the slope. Such slope stability depends on the combined effects of soil and rock properties, the hydrological environment, the slope's geometry, any existing reinforcement, the loading conditions, and the seismicity of the region. With the rise in construction and development activities, a number of projects are being developed in potential slope failure areas. Therefore,it is crucial for geotechnical engineers to anticipate and make a quick estimate of the stability of slopes before undertaking a trustworthy and economical design. Various machine learning algorithms have been effectively applied in several slope stability projects in recent years. Sakellariou & Ferentinou [1] investigated the concept of prediction analysis and created a relationship between the various slope parameters using an artificial neural network (ANN). Ray et al. [2] presented the application of machine learning techniques to predict the stability of slopes under the jointed rock and residual soil located in the Himalayan regions of Uttarakhand and Himanchal Pradesh using 400 datasets for soil slope and 1200 datasets for rock slopes obtained from numerical modelling. Kumar et al. [3] used datasets of 216 slopes as obtained from numerical modelling in the finite element-based method to forecast the factor of safety of a dragline dump slope using an ANN-based machine learning model and multiple linear regression analysis. Qi & Tang [4] performed a comparative study for the use case of different meta-heuristic and machine learning algorithms. Gaussian process regression (GPR), multiple linear regression (MLR), multi layer perceptron (MLP), simple linear regression (SLR), and support vector regression (SVR) were used with 630 finite limit equilibrium analysis data to forecast the stability of the slope [5]. Gelisli et al. [6] performed a 100 slopes model and calibrated artificial neural network (ANN) algorithms to predict the factor of safety using the height of slope, water table, angle of slope, unit weight of the material, cohesion and internal friction angle as input parameters. Samui [7] used the support vector machine for the predicion of slope stability as a regression and classification problem and found that the support vector machine performed better than the ANN with an accuracy of 85%. Recently, the suitability of eleven machine learning algorithms for support vector regression (SVR), bayesian ridge (BR), linear regression (LR), elastic net regression (ENR), k nearest neighbour (KNN), Bagging, adoptive boosting regression (ABR), gradient boosting machine (GBM), random forest (RF), decision tree (DT), extra tree regression (ETR)) had been assessed by Lin et al.[8] with c, ϕ, γ, H, r_u and θ as input to predict the stability of slope on 349 slope datasets. On a South Korean slope dataset of 6828, Hwang et al. [9] used a decision tree to examine the slope factor. Mohamed et al. [10]used a fuzzy logic system to compute safety factors using 126 data-sets collected from Geo-studio software with five input features: slope height, unit weight, slope inclination, cohesion, and internal friction angle. Liu et al. [11] used an extreme learning machine to predict slope stability and compared its predictive power to that of a generalized regression neural network. Pradhan [12] predicted the Cameron catchment area's landslide susceptibility using frequency ratio, fuzzy logic, and multivariate regression.

2. Methodology

To generate data-sets for machine learning, several slopes are analyzed in Slide, a limit equilibrium software. A total of 4208 data-sets are used for developing nine different machine learning-based models. Each data-set consists of six input parameters: the cohesion of soil (c), angle of inclination of slope (θ), the height of slope (H), pore water pressure ratio (r_u), friction angle of soil (ϕ), and unit weight of soil (γ). Table 1 gives the statistical summary of all input and output variables used for the study. Slope height (H) as indicated in Figure 1 varies from 10m to 35m with a standard deviation of 9.27. Slope inclination (θ) is the angle of slope with respect to horizontal which deviates within range of 20°to 45°.The output variable is the factor of safety, which is determined by five well-established limit equilibrium methods of Bishop, Morgenstern-Price, Fellenus, Spencer, and Janbu, as presented in Figure 1. Total datasets (4208) are divided into two groups as training and testing subsets each containing 80% of data and 20% of data respectively. The total datasets are checked to identify any correlated features so that redundant columns can be dropped out from the prediction models.

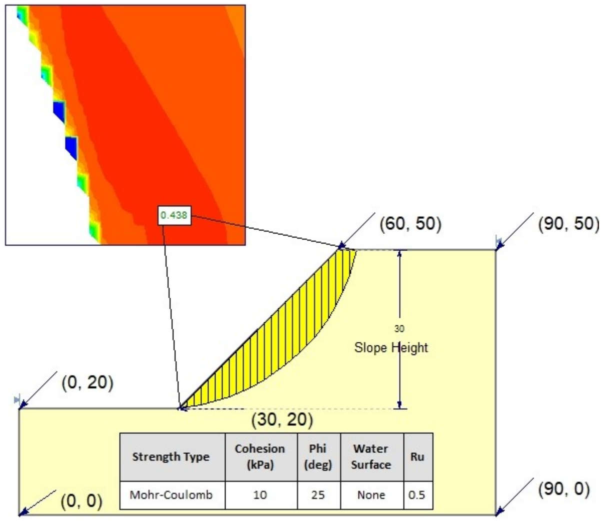

Figure 1: Model developed in Slide to generate FOS data sets

Table 1: Input and output variables for Machine Learning models.

Symbol	Category	Count	Mean	Min	Max	σ
H	Input	4208	22.23	10	35	9.27
θ	Input	4208	35.43	20	45	7.27
c	Input	4208	10.06	0	20	2.91
ϕ	Input	4208	25	15	35	3.01
γ	Input	4208	20	15	25	1.5
r_u	Input	4208	0.485	0	1	0.12
FOS	Output	4208	0.673	0.2	1.95	0.23

A heat map of the correlation coefficient (Figure2) shows that there is no strong positive or strong negative correlation between input variables. The data features don't include any redundant variables. Hence, these input parameters can be used as features for prediction models.

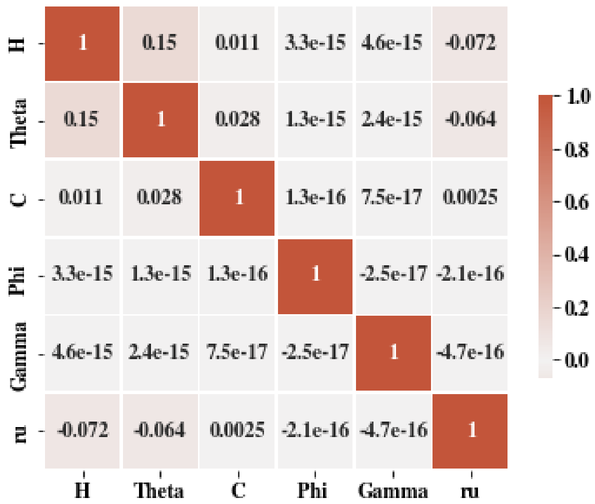

Figure 2: Correlation plot of input features.

Two categories of supervised machine learning algorithms are used for this study. Multiple linear regression and artificial neural network are used as regression models and decision tree, support vector, logistic regression, gradient boosting,Naive Bayes, random forest, and artificial neural network are used as classification models. Supervised regression models are used to predict the factor of safety for given input features such as cohesion, angle of internal friction, pore water pressure, and unit weight of slope material, and supervised classification models are used to classify the slope into safe and unsafe for given input parameters. Figure 3 shows the overall methodology adopted for developing predictive models. The performance of each model is assessed by using various statistical matrices like coefficient of determination (R^2), accuracy, precision, F-1 score, and recall.

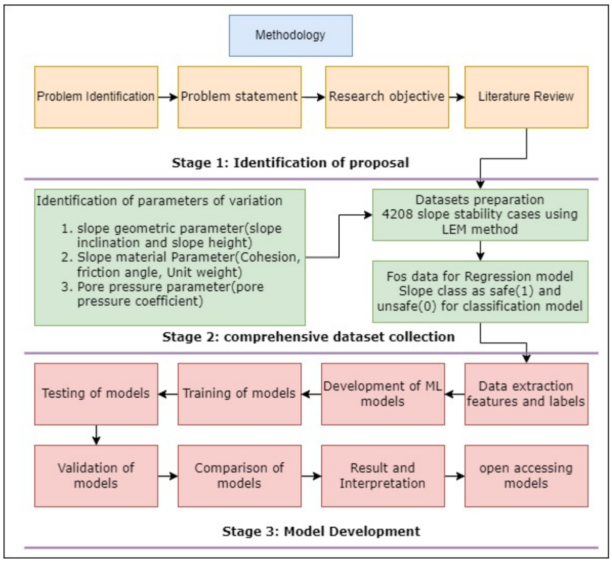

Figure 3: Algorithm for development of ML-based model for slope stability prediction

3. Result and Discussion

Two regression models and seven classification models are used in the course of the study. The performance and predictability of each of these models are discussed in the section below.

3.1 Regression Models

The factor of safety values obtained by Bishop's method, Fellenius, Spencer's, Janbu's, and Morgenstern-Price's methods for training data-sets are utilized to create regression models. Five independent regression models have been developed for both MLR and ANN. MLR model gives a prediction formula for FOS determination, and the ANN model gives neural network weights and biases to predict FOS for given input parameters.

From the multiple linear regression analysis, it is found that the fit of the regression line for each method is good with a coefficient of determination of 0.942, 0.948, 0.946, 0.925, and 0.924 for Morgenstern-Price, Bishop, Janbu, Fellenius, and Spencer approaches respectively. Figure 4 shows the bar plot for each method with their regression coefficient. All these models are fitted with

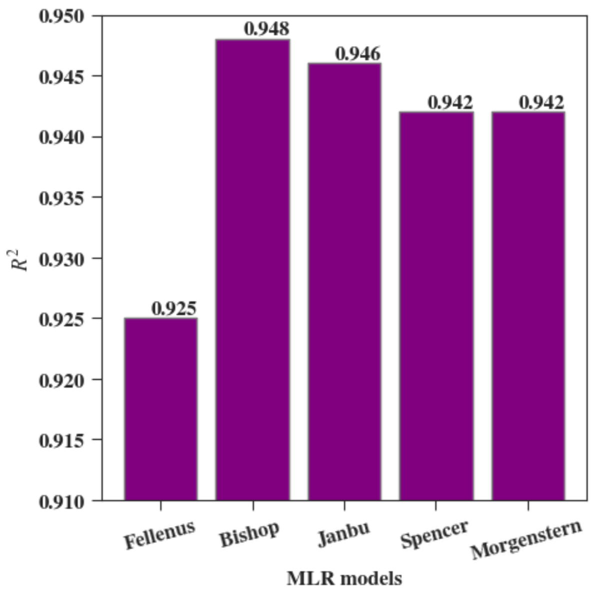

Figure 4: Coefficient of determination for various methods using MLR

multivariate input features with a coefficient of determination value greater than 0.9. The prediction equation based on the MLR model for each method is presented in equations (1), (2), (3), (4), and (5). The parametric variation of output with input features as predicted by MLR-based equations for the mean value of the input is presented in Figures 5 and 6.

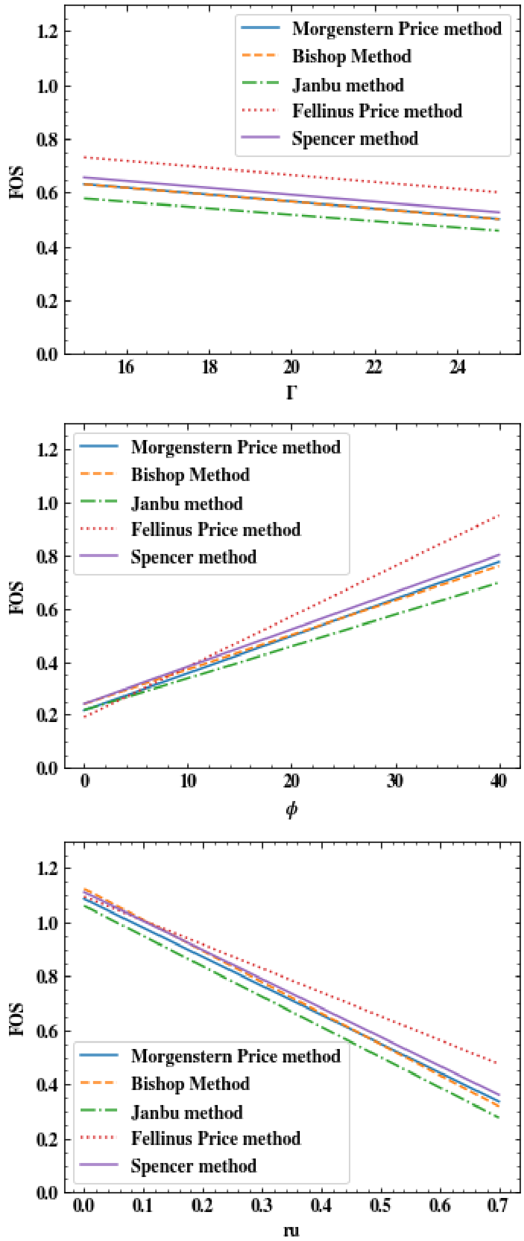

Figure 5: Variation plot of input features with output based on MLR prediction for a mean value of input feature.

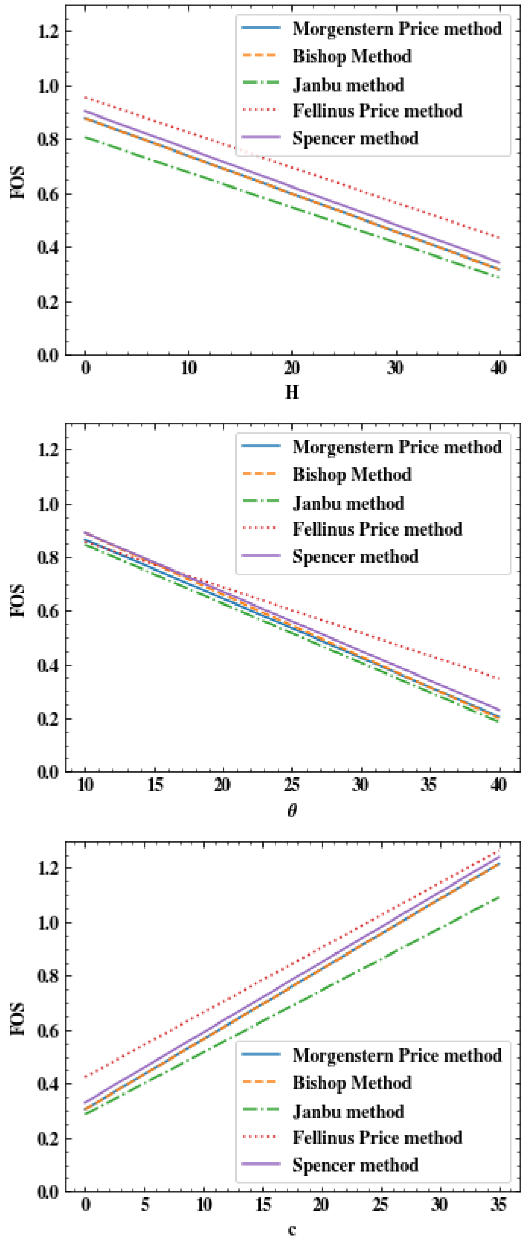

Figure 6: Variation plot of input features with output based on MLR prediction for a mean value of input feature.

Morgenstern-Price:

$$FOS = 1.858 - 0.014H + 0.026c + 0.014\phi - 0.022\theta - 1.072r_u - 0.013\gamma \quad (1)$$

Bishop:

$$FOS = 1.924 - 0.014H + 0.026c + 0.013\phi - 0.023\theta - 1.151r_u - 0.013\gamma \quad (2)$$

Janbu:

$$FOS = 1.838 - 0.013H + 0.023c + 0.012\phi - 0.022\theta - 1.12r_u - 0.012\gamma \quad (3)$$

Fellenius:

$$FOS = 1.530 - 0.013H + 0.024c + 0.019\phi - 0.017\theta - 0.885r_u - 0.013\gamma \quad (4)$$

The best performing neural network is obtained by making a trial on a combination of hidden layers and associated numbers of neurons on each layer, with activation function and optimizer. Several iterations have been performed to obtain the minimum value of mean absolute error (MAE) and the maximum value of R^2 on both training and testing data-sets. A hidden layer with ten neurons is chosen as the best model without additionally increasing the complexity of the model architect. The sigmoid activation function and the Adam optimizer with a learning rate of 0.01 are used for the best performing model. The number of neurons on the input layer and output layer is restricted as per the number of input variables and output variables. The input layer consists of six neurons, and the output layer consists of one neuron. The regression plot for training and testing data sets for the artificial neural network is shown in Figure 7. For all models tested under similar conditions, the Spencer method gives a higher performance in both training ($R^2 = 0.966$) and testing ($R^2 = 0.973$) data-sets with a coefficient of determination (R^2) being very close to 1.

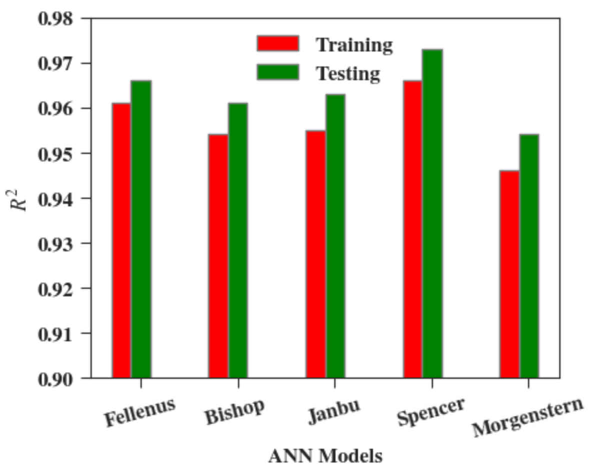

Figure 7: Bar plot for the coefficient of determination for the ANN model

Figure 8 shows the scatter-plot of the predicted factor of safety ($\hat{y}_i$) on the Y-axis and the actual factor of safety (y_i) on the X-axis for each training and testing data-set by the Spencer model. Figure 9 shows the loss curve for best performing Spencer method for twenty number of epochs. From the linear trend of the predicted and actual factor of safety as visible in the scatter-plot, it can be concluded that the artificial neural network regression model is sufficiently capable of predicting the factor of safety value.

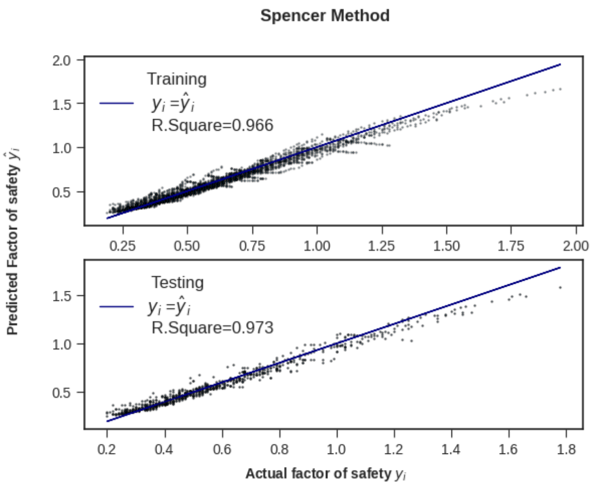

Figure 8: Plot of predicted and target output

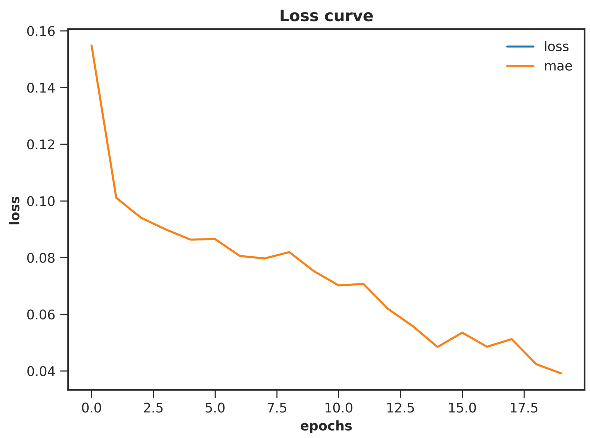

Figure 9: Loss curve with epoch for Spencer method

3.2 Classification Model

The performance of each machine learning classification technique is presented in Figure 10. All seven machine learning classification models demonstrate an accuracy of more than 90% for both testing and training data-sets, which indicates that all seven classification models can well predict the stability of the slope . Table 2 presents different performance indices for all machine learning classification models. For assessing the best model, a prediction score is assigned to the model based on its performance indicators. The model with the higher performance indicator receives a higher score. In the overall rating, the ascending sequence of performance is NB, RF, GBC, LR, ANN, SVC, and DT. The best performing model among all is the DT model, as it gets the highest score of 25, while the NB model is the lowest performing model with a score of 6. DT, ANN, and SVC are the best models for classifying slope stability problems.

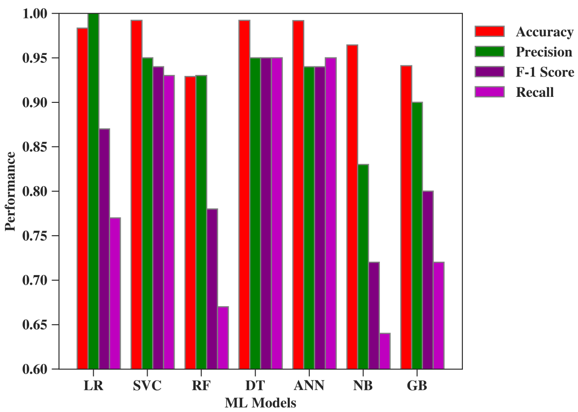

Figure 10: Performance of all machine learning models

Figure 11 shows the confusion matrix as classified from the first ranked decision tree classification model. Out of 842 total test data-sets,

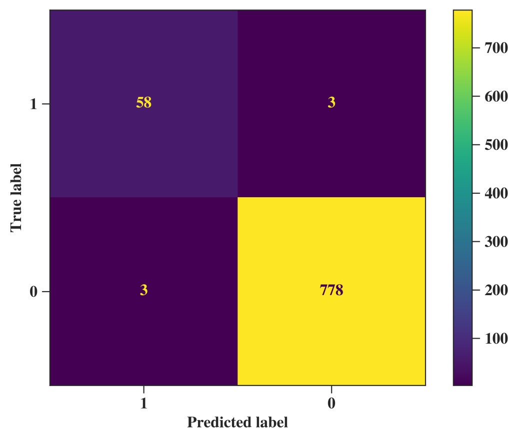

Figure 11: Confusion Matrix for Decision tree Classifier

- 58 data are true positives as actually stable slopes are truly labelled as stable by the DT classification model.
- 3 data are false negatives as actually stable slopes are labelled falsely as unstable by DT the classification model.
- 3 data are false positives as actually unstable slopes are falsely labelled as stable by the DT classification model.
- 778 data are true negative as actually unstable slopes are truly labelled as unstable by the DT classification model.

Table 2: Performance measurements of classification Models

	ML Models	LR	SVC	RF	DT	ANN	NB	GBC
Indicator	Accuracy	0.98	0.99	0.92	0.99	0.99	0.96	0.94
	Precision	1	0.95	0.93	0.95	0.94	0.83	0.9
	F-1 Score	0.87	0.94	0.78	0.95	0.94	0.72	0.8
	Recall	0.77	0.93	0.67	0.95	0.95	0.64	0.72
Score	Accuracy	4	6	1	7	5	3	2
	Precision	7	5	3	5	4	1	2
	F-1 Score	4	5	2	7	5	1	3
	Recall	4	5	2	6	6	1	3
	Total	19	21	8	25	20	6	10
	Overall Rank	4	2	6	1	3	7	5

4. Limitations

Some restrictions have been put in place for data-set collection and model development in order to narrow the focus area. The limitations of study are discussed below.

- The study's chosen input parameter range limits the inputs to the models.
- Throughout the sloped boundary, uniform, homogenous soil conditions are taken into account.
- Effect of water table is represented by the pore pressure coefficient, which may not make perfect sense if the piezometric line is known.
- The effects of external loading conditions and the dynamic effect of the earthquake are not taken into account in this work.
- The prediction performance of these models are evaluated using testing data-sets(20% of total data-sets) which further can be assessed with real data-sets.

5. Conclusion

The major problem of slope stability can be effectively predicted using machine learning tools. To achieve the objective of this study, nine supervised machine learning-based models were developed. Among the nine machine learning models, two regression models (MLR and ANN) can be used for finding FOS value, and seven (NB, RF, GBC, LR, ANN, SVC, and DT) classification models can be used for slope stability classification as stable and unstable. As a result of this study, the following conclusions are drawn:

- Machine learning-based algorithms can serve as better prediction tools for analyzing the stability of slopes.
- FOS as obtained from the ANN model and MLR is in close agreement with target output as generated from limit equilibrium methods.The ANN regression model developed for the Spencer method predicts most accurately both for training and testing data-sets with a coefficient of regression of 0.966 and 0.973 for training and testing respectively.
- The precision of all classification models is higher than 90% except for NB which has 83%.
- In terms of accuracy, all classification models have an accuracy of greater than 90%, so the machine learning classification model can be used with higher performance for slope classification.
- The ascending order of prediction capability of these models based on the score is DT, SVC, ANN, LR, GBC, RF, and NB.

Based on the overall study, the models' predictions are good enough to classify the slope as stable or unstable based on FOS.

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