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Research Article

Random Forest Importance-Based Feature Ranking and Subset Selection for Slope Stability Assessment using the Ranger Implementation

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Abstract

Stability problems of slopes can arise from various factors such as geometrical, geological, seismic etc. For many years, conventional methods such as limit equilibrium method, numerical methods, and statistical methods have been successfully utilized to predict the stability of slopes. On the other hand, several machine learning (ML) attempts have been made for predicting slope stability using datasets available in the literature. The present study aims to build classification models for the assessment of the stability of slopes using the Ranger algorithm. A total of 168 cases with six input parameters (slope height, unit weight, slope angle, cohesion, pore water pressure ratio, and internal friction angle) are used to generate models. In the first step, random forest (RF) feature importance scores of the six features are determined and five different prediction models were produced by reducing the feature numbers of the dataset. The developed models are then assessed using performance metrics and results are compared to choose the best prediction model. According to the obtained results, the feature importance-based feature ranking and subset selection approach (i.e., RF feature importance) affect the performance of the models. It is observed that from the RF feature importance scores, the unit weight is found to be the most influencing feature that affects the stability of slopes for the studied dataset. In addition, the Ranger model developed with five features (Model IV) achieves the highest test accuracy with a value of 90%.

Keywords: Feature Ranking, Machine Learning, Prediction Model, Ranger, Slope Stability

Ranger Uygulamasını Kullanarak Şev Stabilitesi Değerlendirmesi için Rastgele Orman Öneme Dayalı Öznitelik Sıralaması ve Alt Küme Seçimi

Öz

Şevlerin stabilite sorunları geometrik, jeolojik, sismik vb. çeşitli faktörlerden kaynaklanabilir. Şevlerin stabilitesini tahmin etmek için uzun yıllardır limit denge yöntemi, sayısal yöntemler ve istatistiksel yöntemler gibi geleneksel yöntemler başarıyla kullanılmıştır. Öte yandan, şev stabilitesini tahmin etmek için literatürde bulunan veri setlerini kullanılarak pek çok makine öğrenimi (ML) girişiminde de bulunulmuştur. Bu çalışma, Ranger algoritmasını kullanarak şev stabilitesinin değerlendirilmesi için sınıflandırma modelleri oluşturmayı amaçlamaktadır. Model oluşturmak için altı girdi parametresi bulunan (eğim yüksekliği, birim hacim ağırlık, eğim açısı, kohezyon, boşluk suyu basıncı oranı ve iç sürtünme açısı) toplamda 168 şev vakasından oluşan bir veri seti kullanılmıştır. İlk adımda, altı özelliğin rastgele orman (RF) öznitelik önem dereceleri belirlenmiş ve veri setinin değişken sayıları azaltılarak beş farklı tahmin modeli üretilmiştir. Geliştirilen modeller daha sonra performans metrikleri kullanılarak değerlendirilerek ve en iyi tahmin modelini seçmek için sonuçlar karşılaştırılmıştır. Elde edilen bulgulara göre, öznitelik önemine dayalı değişken sıralaması ve alt küme seçimi yaklaşımı (yani RF öznitelik önem derecesi) modellerin performansını etkilediği görülmüştür. RF öznitelik önem puanlarından, çalışılan veri seti için şev stabilitesini en çok etkileyen değişkenin birim hacim ağırlık olduğu görülmüştür. Ayrıca beş değişken ile geliştirilen Ranger modeli (Model IV) %90 değeri ile en yüksek test doğruluğuna ulaşmıştır.

Anahtar Kelimeler: Öznitelik Sıralaması, Makine Öğrenimi, Tahmin Modeli, Ranger, Şev Stabilitesi

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1. Introduction

Slope stability is a critical topic of geotechnical engineering that plays a vital role in ensuring the safe and stable use of land for various purposes, such as infrastructure, residential, and industrial development. The term refers to the ability of a soil or rock slope to resist failure or collapse, which can have catastrophic consequences in areas prone to natural disasters such as earthquakes and landslides. As it affects the safety of people, property, and the environment, the assessment and prediction of slope stability are therefore essential in preventing and mitigating the risk of slope failures. The results of these assessments are used to identify potential problems and make recommendations for remedial measures to improve the stability of the slope.

There have been numerous methods for the evaluation and prediction of slope stability. Existing literature studies have already reported the use of evaluation methods, including limit equilibrium method (LEM), the characteristic line method, the limit analysis method, and the numerical modeling (Yang and Yin, 2004). LEM is one of the widely preferred methods for the assessment of slope stability due to its simplicity in application and analysis methodology (Lim et al., 2016; Jellali and Frikha, 2017; Cala and Flisiak, 2020). However, LEM inherently has some limitations despite being widely applied in practice. Also, LEM is not reliable where nonhomogeneous and anisotropic stratifications exist which generally include geotechnical uncertainties (Krahn, 2003; Xiao et al., 2018; Wang et al., 2020). Other studies have focused on developing sophisticated numerical models and methods for predicting slope failures, considering the complex and dynamic nature of soil and rock slopes. These mentioned models incorporate factors such as soil strength, groundwater conditions, and seismic activity, providing a more comprehensive picture of slope stability. Additionally, these are also useful for identifying the most critical failure modes and developing effective remedial measures to prevent slope failure. Briefly, numerical approaches provide valuable information about the slope's behavior over time, allowing engineers to develop more accurate predictions about its stability.

One of the recent advancements in the area of slope stability is the application of machine learning (ML) algorithms for evaluation and prediction. ML algorithms have been increasingly used for the analysis of large data sets and the prediction of various geotechnical parameters, including slope stability. These algorithms are capable of recognizing patterns and relationships in data and can be trained to make predictions based on this information (Alpaydin, 2020). Several studies have reported the potential of ML applications for evaluating the stability of slopes. For example, Samui (2008) evaluated the applicability of a support vector machine (SVM) for predicting the stability of slopes. Choobbasti et al. (2009) considered artificial neural network (ANN) for the prediction of slope stability in a specified location based on multilayer perceptron networks (MLP). Another study by Liu et al. (2014) used extreme learning machine (ELM) to investigate and evaluate the prediction of the stability of slopes. Abdalla et al. (2015) employed an MLP-ANN model to forecast the minimum factor of safety of slopes under static load for different data sets. Hoang and Pham (2016) evaluated historical earth slope cases using firefly algorithm (FA) and the least squares support vector machine (LSSVM). Chakraborty and Goswami (2017) investigated the prediction of slope stability using the ANN model. Hoang and Bui (2017) applied ELM, radial basis function neural network (RBFANN), and LSSVM algorithms to conduct a comparative study for slope stability assessment. Moayedi et al. (2019) examined the applicability and proficiency of various ML models in predicting slope stability. Pham et al. (2021) built ensemble-based stability prediction models based on 153 slope cases documented in published literature. Kardani et al. (2021) proposed artificial bee colony-optimized ML models based on a hybrid stacking ensemble approach to predict the stability of slopes. More recently, Lin et al. (2022) trained different ensemble learning approaches to build classification models for 444 slope cases and analyzed the prediction efficiency of the models. Wang et al. (2023) built different ML models using classical algorithms combined with dimension reduction methods for slope stability. Yang et al. (2023) performed a comparative analysis for slope stability using different ML algorithms by employing intelligent algorithm optimization. The studies highlight the potential of these techniques in providing accurate predictions of slope stability and showcase their effectiveness in the field of geotechnical engineering. In conclusion, ML algorithms are a promising tool for the prediction and evaluation of slope stability. However, future studies are needed to further explore the potential of ML algorithms in the field of slope stability and to evaluate their performance under different conditions. To this end, in this study, a feature ranking and a subset selection methodology using the RF feature importance were employed to generate prediction models. In general, feature ranking refers to the ordering of original features for a specific evaluation criterion, which is usually a step of feature selection. It is employed to determine which features are more important (Liu et al., 2022). A total of five different prediction models (i.e., Model I, II, III, IV, and V) were created based on the importance scores of the six features of the studied dataset for reducing the number of features.

The overall objective of this paper is to propose a slope stability prediction model by using RANdom forest GEneRator (Ranger), which is one of the implementations of the random forest (RF) algorithm. Hence, The Ranger implementation was used at the model prediction stage for each feature ranking and different models were produced for each ranking result. In this present study, in order to learn the best performance of the model, prediction models were evaluated through performance metrics (Accuracy, Recall, Precision, and F1-Score) and results were compared to demonstrate the best model that produced higher prediction performance.

2. Material and Method

2.1. Dataset Information

In this research, the dataset based on published literature (Sah et al., 1994, Lu and Rosenbaum, 2003, Zhou and Chen, 2009; Li and Wang, 2010, Xiaoming and Xibing, 2011) is used to create ML models. The dataset contains several field case histories obtained from different sites. A list of the slope cases can be found in Hoang and Pham (2016). The whole dataset comprises 168 slope cases, including 84 "stable" *(Yes)* and 84 "unstable" *(No)* slope cases. The features of the dataset are unit weight (γ), slope height (*H*), slope angle (β), cohesion (*c*), pore water pressure ratio (r_u), and angle of internal friction (ϕ). *H* is the vertical distance between the slope crest and the slope base. β is the angle that is computed based on the inclined plane and the base plane. γ refers to the weight of a unit volume of soil. it is determined by the weight of the soil and the volume of the soil sample. c is one of the main shear strength parameters of soils or rocks with regard to the well-known Mohr-Coulomb failure criterion. ϕ is another soil or rock strength parameter that indicates its ability to withstand shear stresses. r_u is computed by dividing the pore water pressure by the overburden pressure. It should be noted that the r_u value in the last case (168th case given by Hoang and Pahm, 2016) is considered to be 0.45 since the minimum and maximum values of r_u should range between 0 and 1.0. Table 1 summarizes the information of the statistical descriptions of the features. Moreover, Fig. 1 shows the Pearson correlation matrix among six input features to clearly demonstrate the pairwise relationship between input features with the corresponding correlation coefficients. For this dataset, the correlation coefficient ranges between minimum -0.14 and maximum 0.63; thus, it can be concluded that there are no noteworthy correlations between each feature.

Table 1. Descriptive statistics

Features	Ave.	St.Dev.	Min.	Med.	Max.
γ	21.8	4.1	12.0	21.0	31.3
c	34.1	46.0	0.0	20.0	300.0
ϕ	28.7	10.6	0.0	30.2	45.0
β	36.1	10.2	16.0	35.0	59.0
H	104.2	133.1	3.6	50.0	511.0
r_u	0.2	0.2	0.0	0.3	0.5

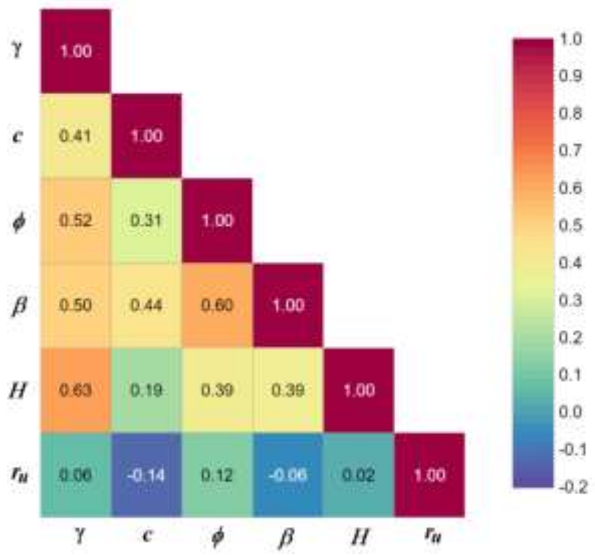

Figure 1. Illustration of the Pearson correlation plot

2.2. Feature Importance (FI) Analysis

This section presents FI analysis to examine the role of each influence variable in slope stability analysis. FI analysis is an essential process that can be considered in model interpretability and feature selection in ML. It is used to determine the most significant features or variables that contribute to the target variable. In other words, it helps to determine which variables have the most significant impact on the outcome of the model. In this study, the RF algorithm is applied to the train dataset to show the influencing features for slope stability analysis. The feature importance of all the six input features and their arrangement from top to bottom is given in Fig. 2. It can be seen that the unit weight (γ) is the most important feature influencing slope stability for this dataset. This means that the unit weight plays a key role in the evaluation of slope stability for the studied dataset. Moreover, cohesion (c) is the second most important feature among the other four features, followed by H, ϕ, β, and r_u. It is also worth mentioning that different FI scores may be obtained when different ML algorithms and datasets are employed (Guyon et al., 2008).

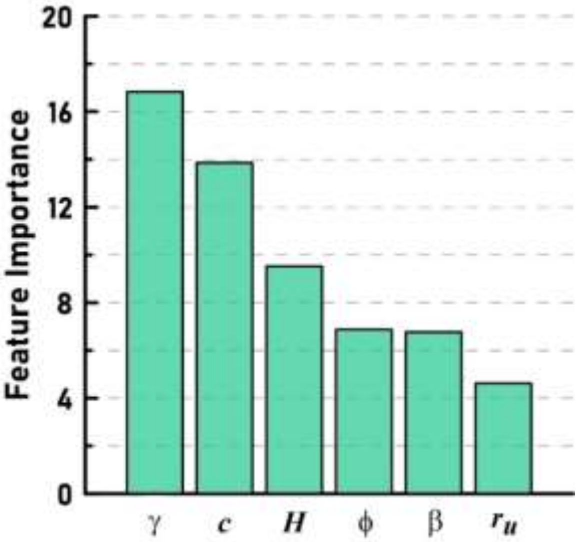

Figure 2. FI variation of the influencing features

2.3. RANdom forest GEneRator (Ranger)

Ranger, nearly equivalent to random forest (RF), is a fast implementation of the RF model. It supports classification, regression, survival and probability trees (Wright and Ziegler, 2015). Ranger is designed to be fast and memory-efficient, and it also uses a number of optimizations and parallel processing techniques to achieve this. For instance, Ranger is parallelizable, which allows it to take advantage of multiple processors to build the trees more quickly (Tiyasha et al., 2021). It applies a modified version of the binary search algorithm to quickly find the best split points for each feature, which reduces the computation time compared to other implementations of random forests (Hobeichi et al., 2022). Ranger is designed to use as little memory as possible, which makes it suitable for high-dimensional datasets that cannot fit in memory (Moon et al., 2022). The prediction error is obtained from the out-of-bag (OOB) samples. This eliminates the need for a separate validation set, which can save time and reduce the risk of overfitting.

2.4. Building ML Models

The slope dataset was divided into the training (70%) and test datasets (30%) using simple random sampling (Demir and Sahin, 2022) for model production and performance analysis. The training set was utilized for building ML models, whereas the test set was used for performance evaluation. In this study, five different prediction models were created including 2 to 6 features with respect to the ordered FI scores given in Fig. 2. Feature selection was conducted manually based on the FI scores and model performances were assessed considering the selected features to investigate the performance result of the models with various features. Table 2 presents the five prediction models with variable features. After the model structures were built, the Ranger algorithm was applied to predict slope stability and the performance measurements of the models were obtained with regard to four performance metrics to select the best model.

Table 2. Considered ML models with various features

	Prediction Models				
	Model I	Model II	Model III	Model IV	Model V
Features	γ	γ	γ	γ	γ
	c	c	c	c	c
		H	H	H	H
			ϕ	ϕ	ϕ
				β	β
					r_u

2.5. Building ML Models

The "*Ranger*" package in R software was applied in the study. Repeated 10-fold cross-validation (three times) and grid search was employed for tuning and determining the optimal hyperparameters of each model. Some hyperparameters of the Ranger algorithm (i.e., *mtry*, *ntree*) that should be tuned before model generation are given in Table 3. While *'mtry'* refers the number of variables available for splitting at each tree node, *'ntree'* represents the number of trees to grow. For all models, *'ntree'* and *'min.node.size'* were held constant at a value of 500 and 1.0, respectively. The final values of the hyperparameters used for the models are provided in Table 3.

Table 3. List of optimal hyperparameters of the models

Models	Features	Parameters	Best Value
Model I	γ, c	*mtry*	2
		ntree	*500*
		splitrule	*extratrees*
		min.node.size	*1*
Model II	γ, c, H	*mtry*	3
		ntree	*500*
		splitrule	*gini*
		min.node.size	*1*
Model III	γ, c, H, ϕ	*mtry*	4
		ntree	*500*
		splitrule	*gini*
		min.node.size	*1*
Model IV	γ, c, H, ϕ, β	*mtry*	5
		ntree	*500*
		splitrule	*gini*
		min.node.size	*1*
Model V	γ, c, H, ϕ, β, r_u	*mtry*	4
		ntree	*500*
		splitrule	*extratrees*
		min.node.size	*1*

2.6. Performance Measurements

The performance of the prediction models is evaluated using four metrics based on the confusion matrix (CM), namely Accuracy (*Acc*), Precision (*P*), Recall (*R*), and F1-Score (*F1*). CM is a specific table that allows visualization of counts correctly and incorrectly predicted by the model. The stable cases were regarded as positive class samples and the unstable cases as negative class ones. All metrics used for performance measurement take values in the range of 0 and 1. The details of the metrics are provided in Table 4.

Table 4. Performance evaluation metrics

		Reference		
		Yes	No	
Predicted	Yes	TP	FP	TP: True Positive FP: False Positive
	No	FN	TN	TN: True Negative FN: False Negative

Metrics	***Accuracy (Acc)***:	TP + TN/ (TP+TN+FP+FN)
	Precision (P):	TP/ (TP+FP)
	Recall (R):	TP/(TP+FN)
	F1-Score (F1):	(2*xPxR*)/(*P*+*R*)

3. Results

The experimental results are depicted in Fig. 3. For comparison, different evaluation metrics discussed in Section F were used to thoroughly display prediction results. It was observed the following outcomes from Fig. 3: (i) Accuracy represents the ratio of the number of correctly predicted samples to the total samples. It is clearly seen that different feature subsets have an impact on the model test accuracies. *Acc* increases as the feature number increases up to five features. At this point, the highest *Acc* value is achieved with the value of 90% for Model IV. Thereafter, *Acc* decreased from Acc=90% to 82% when all features of the dataset are used (i.e., Model V). (ii) Precision indicates the number of actual "Yes" predictions that actually belong to all samples categorized as "Yes" class. Higher *P* reveals that "Yes" classes are better predicted than "No" classes in the classification model. Model IV is the best performer (*P*= 95.45% for five features) and can be easily visible in the figure. For the other models, *P* values are 95%, 84.62%, 84%, and 80% for Model III, Model II, Model V, and Model I, respectively. (iii) Recall is the ratio of all classes (i.e., "Yes" and "No") that are properly classified. A higher *R* value indicates that the majority of the positive classes are categorized as "Yes" classes. Model II outperformed the other models with a score of 88%, followed by 84% for Model IV, 80.77% for Model V, 80% for Model I, and 76% for Model III. (iv) F1-Score is the harmonic mean of the *R* and *P*. The higher *F1* value depicts the model is in making predictions more accurately. *F1* values of the generated models were found to be from highest to lowest as 89.36% for Model IV, 86.27% for Model II, 84.44% for Model III, 82.35% for Model V, and 80% for Model I, respectively. As a result, performance metrics indicate that the performance of Model IV is better than the other models. Moreover, Model II exhibits similar performance to Model III in the case of three and four features used. Therefore, the ϕ feature has no significant effect on the model performance, neither positive nor negative. The worst model performance in predicting slope stability is found for Model I which has the lowest feature numbers.

4. Conclusions

In this paper, a feature importance-based feature ranking and subset selection framework was presented for slope stability assessment. The Ranger algorithm was utilized during the generation of the prediction models. Feature selection was conducted manually based on the random forest FI scores and

Model I		Actual: Yes	Actual: No
Predicted	Yes	20	5
	No	5	20
Accuracy		0.8000	
Precision		0.8000	
Recall		0.8000	
F1-Score		0.8000	

Model II		Actual: Yes	Actual: No
Predicted	Yes	22	4
	No	3	21
Accuracy		0.8600	
Precision		0.8462	
Recall		0.8800	
F1-Score		0.8627	

Model III		Actual: Yes	Actual: No
Predicted	Yes	19	1
	No	6	24
Accuracy		0.8600	
Precision		0.9500	
Recall		0.7600	
F1-Score		0.8444	

Model IV		Actual: Yes	Actual: No
Predicted	Yes	21	1
	No	4	24
Accuracy		0.9000	
Precision		0.9545	
Recall		0.8400	
F1-Score		0.8936	

Model V		Actual: Yes	Actual: No
Predicted	Yes	21	4
	No	5	20
Accuracy		0.8200	
Precision		0.8400	
Recall		0.8077	
F1-Score		0.8235	

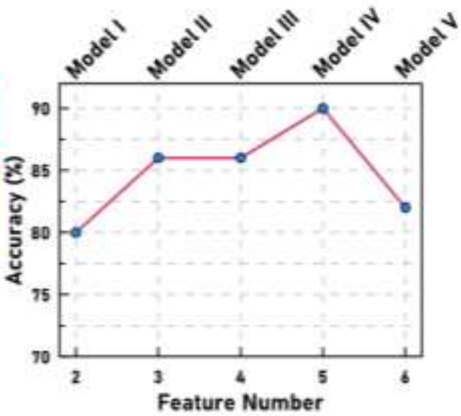

Figure 3. Performance results of five different prediction models

model performances were assessed considering the selected features to investigate the performance result of the models with various features. It is observed that the selected feature numbers affected the prediction results of the models. While Model IV achieved the highest test accuracy with a value of 90%, Model I, which has the lowest features, exhibited the worst performance in terms of performance metrics.

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