Research Article

Ahmed Cemiloglu, Yingying Cao, Arkan K. S. Sabonchi, and Yaser A. Nanehkaran*

Predicting stability factors for rotational failures in earth slopes and embankments using artificial intelligence techniques

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Abstract: This study focuses on slope stability analysis, a critical process for understanding the conditions, durability, mass properties, and failure mechanisms of slopes. The research specifically addresses rotational-type failure, the primary instability mechanism affecting earth slopes. Identifying and understanding key factors such as slope height, slope angle, density, cohesion, friction, water pore pressure, and tensile cracks are essential for effective stabilization strategies. The objective of this study is to develop accurate predictive models for slope stability analysis using advanced intelligent techniques, including data mining mapping and complex decision tree regression (DTR). The models were validated using performance metrics such as mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE), and the coefficient of determination (R^2). Additionally, overall accuracy was assessed using a confusion matrix. The predictive model was tested on a dataset of 120 slope cases, achieving an accuracy of approximately 91.07% with DTR. The error rates for the training set were MAE = 0.1242, MSE = 0.1722, and RMSE = 0.1098, demonstrating the model's capability to effectively analyze and predict slope stability in earth slopes and embankments. The study concludes that these intelligent techniques offer a reliable approach for stability analysis, contributing to safer and more efficient slope management.

Keywords: slope stability, earth-slopes, rotational-type failure, AI algorithms, machine learning

*** Corresponding author: Yaser A. Nanehkaran**, School of Information Engineering, Yancheng Teachers University, Yancheng 224002, Jiangsu, China; Department of Management Information Systems, Faculty of Economics and Administrative Sciences, Cankaya University, Ankara 06790, Türkiye, e-mail: yaser@yctu.edu.cn
Ahmed Cemiloglu, Yingying Cao: School of Information Engineering, Yancheng Teachers University, Yancheng 224002, Jiangsu, China
Arkan K. S. Sabonchi: Technical College, Imam Ja'afar Al-Sadiq University, Baghdad 10011, Iraq

1 Introduction

Slope stability is one of the most important and greatest challenges in geotechnical engineering during various engineering designs and constructions [1–7]. Slope stability refers to the ability of a soil or rock slope to remain in place and resist failure due to the force of gravity [8–10]. The stability of a slope depends on factors such as the strength of the material, the slope angle, the amount and type of vegetation, and the presence of water or other fluids, geo-unit condition, the type of soil or rock, the presence of cracks or other defects, erosion or other processes, and slope internal specification [11–13]. A slope that is not stable can result in sliding, rockfalls, toppling, and other types of mass wasting [14–16]. To assess slope stability, geo-engineers use a combination of field observations, laboratory testing, and modeling to evaluate the factors that affect stability and to determine the likelihood of failures [17]. To ensure stability, engineers may use a variety of techniques, such as soil nailing, anchoring systems, terracing, retaining walls, or the creation of vegetative cover. In some cases, it may be necessary to modify the slope to reduce its angle or to reinforce it with materials such as concrete or steel. The design of these mitigation measures depends on the specific conditions and characteristics of the site and the stability issues it presents [18].

It is important to note that slope stability is a complex and interdisciplinary field, and the assessment and design of slope stability solutions require the expertise of geo-engineers who provide appropriate stabilizations [17]. The goal of slope stability analysis and design is to ensure public safety and prevent damage to property, infrastructure, and the environment [19]. Thus, providing a detailed and accurate stability analysis as well as a proper understanding of the instability mechanism that might happen in slopes can be useful. Geometry, stress–strain history, structural and tectonic conditions, geomorphologic status, regional climate, seismic activity, water conditions, vegetation, weathering, drainage pattern, construction activities, and special occasions all have a direct impact on the type of slope failures and sliding mechanisms [20,21]. Depending on nature of the sliding mass, the slope's failure mechanisms can be classified as wedge, planar, toppling, and rotational (or circular-type) failures [8].

Rotational failure is a common type of slope failure in which a soil mass or embankment material rotates along a curved surface, typically a circular or spiral-shaped failure plane. This type of failure is typically caused by a combination of factors such as soil strength, slope angle, and the presence of water or other fluid in the slope material. The movement of the slope mass can be triggered by changes in the slope conditions such as heavy rainfall, earthquakes, or changes in the water table [22,23]. Also, rotational failure can result in the creation of large circular or spiral-shaped depressions in the slope, which can be shallow or deep and can be several to hundreds of meters in diameter. Figure 1 illustrates the main concept of rotational failure, which occurred in slopes and embankments. The rotational failure process can be gradual or rapid and can cause significant damage to infrastructure and property, as well as pose a risk to public safety [24]. So, accurate estimation of the slope stability can be considered as the main duty for slope or embankment design [25,26].

Numerous approaches have been introduced and used to analyze or predict slope stability with a background of more than 300 years, which include a range of simple evaluations, planar failure, limit state criteria, limit equilibrium analysis, numerical methods, hybrid and high-order approaches, which are implemented in two and three dimensions [27]. These methods have their own certain advantages and limitations that directly affect the stability results [28]. Also, there are various uncertainties that are imposed from stability factors, which have an effect on stability decisions. In this regard, professionals are always looking for new and efficient methods that are capable of reducing the uncertainty rate and increase the accuracy of the calculations. Recently, with the advancement of intelligent technology applications in geotechnics, various machine learning-based methods was successfully applied to predict slope stability and factored parameters subjected to different failure types [29,30]. Table 1 provides a summary of some relative machine learning-based methods that are used in slope stability analysis by researchers. The main objective of the literature on rotational failures on slopes is based on factored parameters that lead to calculation by these methodologies , which are presented in Figure 1 properly. These factors are considered in predictive models by developers to conduct more accurate results. In such cases, the machine learning-based methods are chasing several goals like safety factor (FS), durability status, and stability class or reliability predictions for slopes and embankments. These methods cover extended aspects of machine learning and data mining mapping procedures. In the meantime, complex decision tree regression (DTR) has received remarkable success recently in stability analysis for geotechnical assessments [31–34].

DTR is a type of regression analysis method that uses a tree-like model of decisions and their possible consequences. The goal of DTR is to create a model that predicts a target numerical value based on certain input features. Each internal node of the tree represents a test on an input feature, each branch represents the outcome of the test,

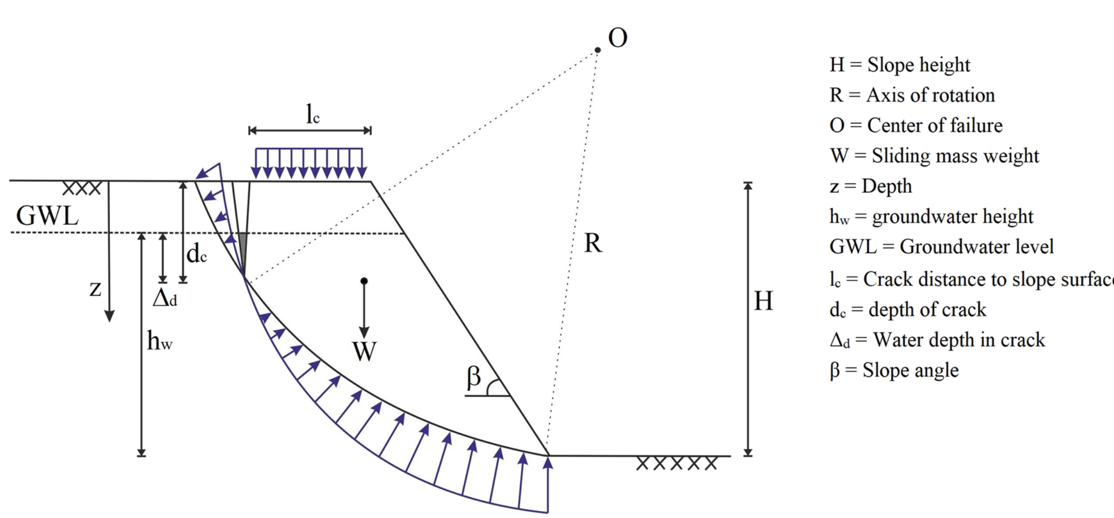

Figure 1: Factored parameters on slope stability subjected to rotational failures.

Table 1: A summary of recent slope stability prediction techniques based on machine learning

Reference	Computational learning methods														Other methods
	MLP	Fuzzy	SVM	GA	ANFIS	RF	DT	k-NN	PSO	MC	GNB	ClM	LR	DNN	
Suman et al. [35]	*								*						
Hoang and Pham [36]			*						*				*		
Xue [37]			*						*						
Kang et al. [38]		*			*					*	*				
Fattahi [39]		*			*					*					
Feng et al. [40]											*				
Rukhaiyar et al. [41]	*								*						
Qi and Tang [42]															
Xu et al. [43]				*											
Bui et al. [44]	*		*									*			
Koopialipoor et al. [45]	*								*				*		Imperialist competitive
Sari et al. [46]			*										*		
Zhou et al. [47]	*		*			*									Gradient boosting
Yuan and Moayedi [48]	*		*				*	*					*		
Gao et al. [49]	*														Imperialist competitive
Zheng et al. [50]				*											Limit equilibrium
Palazzolo et al. [51]				*											
Azmoon et al. [52]	*											*		*	
Zhou et al. [53]		*			*										
Mahmoodzadeh et al. [54]	*		*			*		*					*	*	
Lin et al. [55]						*	*								Gradient boosting
Nanehkaran et al. [56]	*		*			*	*	*							
Mu'azu [57]	*	*			*										
Nanehkaran et al. [58]	*		*			*	*								Limit equilibrium

MLP: multilayer perceptron, Fuzzy: fuzzy logic, SVM: support-vector machines, GA: genetic algorithm, ANFIS: adaptive neuro-fuzzy inference system, RF: random forest, DT: decision tree, k-NN: k-nearest neighbour, PSO: particle-swarm optimization, MC: Monte-Carlo simulations, GNB: gaussian naïve bayes, ClM: clustering method, LR logistic regression, DNN: deep neural networks.

and each leaf node represents a predicted value for the target variable. The prediction of the DTR model is the average value of the target variable of the samples in the corresponding leaf node [59]. DRT models overcome the shortcomings of other data mining mapping techniques by producing a transparent and structural model that explicitly represents the relationship between input and output parameters [60]. The presented study attempted to use a complex DTR predictive model to provide stability prediction based on factored parameters, which was implemented on 120 slope cases in Iran.

Considering the wide range of studies on advanced technologies in slope stability and soil embankment stability analysis, researchers have explored various approaches. These include intelligent systems, decision-making techniques, and machine learning methodologies [61–67], as well as numerous numerical modeling techniques [68–73]. With reviewing the variety of literature, a main gap that professionals face with where this study addresses is the need for more accurate and reliable predictive models for slope stability analysis, specifically focusing on rotational-type failures. While previous studies have explored various methods for slope stability assessment, there has been a lack of research applying advanced intelligent techniques like data mining and complex DTR. This study fills that gap by developing and validating a model that significantly enhances the prediction accuracy and reliability of slope stability assessments.

2 Methods

2.1 DTR principles

The DTR is a tree-like model which uses regression analysis procedures for decisions and their possible consequences [59]. Figure 2 provides a basic schematic diagram of DTR regression trees. DTR is used for both linear and non-linear relationships between the target variable and input features. It can handle high-dimensional input data and

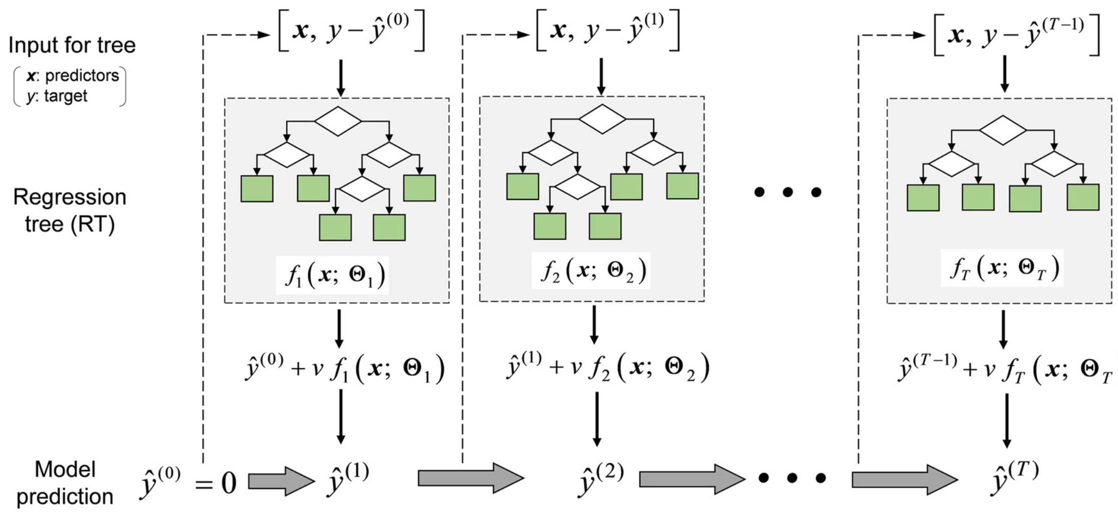

Figure 2: A schematic diagram for a basic DTR [74].

complex interactions between features. One important aspect of decision trees is the process of "pruning" the tree, which involves removing branches that do not contribute much to the accuracy of the model to prevent overfitting [75]. Another aspect to consider is the choice of splitting criterion, such as mean squared error (MSE) or mean absolute error, which determines how the tree splits the data based on the input features. DTR can be sensitive to small variations in the data and can be improved by using ensemble methods such as random forest regressions [59]. DTR has several advantages and disadvantages, which can be used in different aspects of decision-based evaluations [76,77]. Some of the advantages of DTR can be presented as follows [75]:

- *Easy to understand and interpret*: The tree structure of a Decision Tree makes it easy to understand and interpret the relationships between the features and the target variable.
- *Handles non-linear relationships*: Decision Trees can handle complex non-linear relationships between features and target variable.
- *Can handle missing values*: Unlike many other machine learning algorithms, Decision Trees can handle missing values in the data.
- *Not sensitive to outliers*: Decision Trees are not sensitive to outliers in the data, as the splits in the tree are based on the overall distribution of the data.

Also, disadvantages of the DTR are provided as follows [74]:

- *Overfitting*: If a decision tree is not pruned, it can easily overfit the data and perform poorly on new, unseen data,
- *Instability*: Decision Trees can be unstable, as small changes in the data can lead to large changes in the structure of the tree.
- *Bias towards features with many categories*: Decision Trees tend to split more frequently on features with many categories, which can lead to a bias towards these features.

Overall, DTR is a powerful and flexible machine-learning algorithm that can be useful for many regression problems. However, it is important to carefully evaluate the advantages and disadvantages and determine if it is the best approach for a given problem. One of the good aspects of DTR is chasing various scenarios and variables to provide accurate result based on existed information, which are proper circumstances to using in geotechnical aspect and slope stability assessments. In this regard, DTR works by dividing the input data into smaller subsets based on the values of the features and then making predictions based on the average target value of the samples in each subset. The process of dividing the data into subsets is repeated until a stopping criterion is met, such as a minimum number of samples in a leaf node or a minimum decrease in the variance of the target variable. The basic steps in DTR modeling can be presented as follows:

- *Select the best feature to split the data*: The algorithm selects the feature that provides the largest decrease in the variance of the target variable.
- *Divide the data into subsets*: The data is divided into subsets based on the values of the selected feature.
- *Create a new internal node for the selected feature*: The algorithm creates a new internal node for the selected feature and adds the subsets as branches.

- *Repeat the process for each subset*: The process is repeated for each subset until a stopping criterion is met.
- *Create a leaf node for each subset*: Once the stopping criterion is met, the algorithm creates a leaf node for each subset and assigns a predicted target value based on the average of the target values of the samples in that subset.
- The final result of the DTR is a tree-like model that can be used to make predictions for new, unseen data.

2.2 Data acquisition and structured database

The rotational failure for earth slopes and embankments is targeted in this research. The rotational failure is the main failure mechanism that threatens soil slope worldwide, and providing an alternative stability prediction model can be used frequently to cover the analytical gap in traditional stability analysis. As presented in Figure 1, there are several certain factored parameters that have a direct impact on soil slope and embankment's stability, which include slope height, slope angle, density, cohesion, friction, water pore pressure, and tensile crack. These parameters can be categorized into several main triggering groups such as geometric partial factors, geo-materials partial factors, strength partial factors, and water conditions. These factored parameters are imposed on slope stability status, and the durability of slope, which leads to stable or unstable conditions was considered as input parameters. The FS, slope durability status (SDS), and stability class were considered as main output values.

The prepared database from 120 different earth-slope and embankment cases contains seven input variables and three output variables data. The input parameters consist of slope height (H), slope angle (β), density (γ), cohesion (c'), friction (ϕ'), water pore pressure (U), tensile crack (V), and output parameters are FS, SDS, and stability class. The prepared database was randomly divided into testing (30% for the main database) and training (70% for the main database) datasets. The database contains 120 cases, which are segregated into 84 cases for the training dataset and 36 cases for the testing dataset which both stable and unstable slopes are considered. It should be noted that the primary dataset used in this study comprises a variety of case reports from different regions of Iran. These reports were compiled by researchers and professionals and include both literature reviews and technical notes. The input and output parameters, histograms, and statistical features of the discussed database are shown in Table 2. The main statistical indexes used in this study are the minimum (max), maximum (min), mean, standard deviation (Std.Dev.), variance, and skewness values. The main limit state circumstance was selected for FS variation (FS = 1.0), which represents stability class and slope durability. So, for all stability calculations, FS is greater than 1.0, slope is considered as stable; and for FS less than 1.0, slope is considered as unstable. It should be noted that the slope at the $F.S$ is equal to 1.0, the probability of stability status is equal to 50%; so, the state is considered as the critical state.

Additionally, the Variance Accounted For (VAF) was used to indicate how much of the variance in a dependent variable can be explained by one or more independent input variables in a predictive model. In practical terms, VAF helps to understand the proportion of the total variability in the outcome variable that is attributable to the predictors or explanatory variables being studied. So, higher VAF values suggest that a larger proportion of the

Table 2: Statistical features analysis for input and output factored parameters

Parameter	Max	Min	Mean	Std.Dev.	Variance	Skewness	VAF (%)
			Input				
Slope height (m)	25.0	3.50	14.25	8.77	84.59	1.92	88.1
Slope angle (degree)	90.0	32.0	61.00	23.67	90.88	2.21	75.8
Density (kN/m^3)	21.0	17.3	19.15	1.51	80.06	1.84	78.5
Cohesion (kPa)	62.0	0.00	31.0	25.31	64.87	2.20	89.0
Friction (degree)	39.2	30.0	34.6	3.755	25.19	2.13	93.1
Water pore-pressure	0.50	0.00	0.25	0.204	0.042	0.82	71.6
Tensile crack (m)	1.20	0.10	0.65	0.449	0.211	1.05	77.8
			Output				
F.S	2.0	0.0	1.0	—	—	—	—
Stability class	1.0	0.0	1.0	—	—	—	—
SDS	Stable	Unstable	Critical	—	—	—	—

variability in the dependent variable is accounted for by the model, which generally indicates a better fit of the model to the data. It should be noted that VAF is used in machine learning in slightly different ways depending on the context and the specific type of model. The presented study used explained variance value which indicates the proportion of the total variance in the target variable that is captured by the model. It helps evaluate how well the model explains the variability of the target.

2.3 Predictive model implementation

DTR regression is a decision tree algorithm used for the prediction of continuous variables. The algorithm works by recursively splitting the data into subsets based on the features that best explain the target variable. The tree is constructed by repeating the following steps (Figure 3):
– Step 1: Select the feature that provides the highest reduction in variance or mean squared error as the split criteria.
– Step 2: Partition the data based on the selected feature and assign the resulting subsets to child nodes of the current node.
– Step 3: At each leaf node, the prediction is made by computing the mean of the target variable for the samples in that node.
– Step 4: The algorithm continues until a stopping criterion is reached, such as a maximum depth of the tree, a minimum number of samples required at a leaf node, or a minimum reduction in variance or MSE at each split.
– Step 5: Once the tree is built, predictions can be made by traversing the tree to find the leaf node that best fits the input data and returning the mean prediction for that node.

These steps are implemented in stability analysis based on input parameters to get output results, which was implemented in the Python high-level programming language. Used hyperparameters for DTR include the maximum depth of the tree, the minimum number of samples required at a leaf node, and the criteria used to determine the best split at each node (such as MSE or variance reduction). Hyperparameters are commonly used to optimize the fitting process which can increase the machine learning model prediction accuracy. These hyperparameters can be tuned through methods such as cross-validation to find the optimal combination for a given problem. Using hyperparameters increases the learning rate and overall

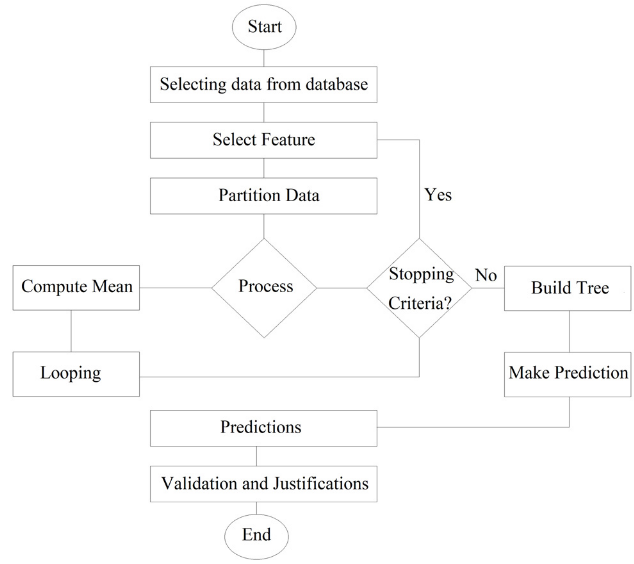

Figure 3: Process flowchart of the implemented DTR method.

accuracy estimation in machine learning algorithms. The model learning rate (test/train ratio) is a response to estimated errors each time the model weights are updated. In fact, how quickly the model adapts to the problem is controlled by the learning rate. While larger learning rates result in rapid changes and require fewer training epochs, smaller learning rates require more training epochs due to smaller changes to the weights at each update. In particular, the learning rate is used configurable hyperparameters [78]. It has a small positive value, usually between 0.0 and 1.0. The learning rate used in this study was selected by optimizers, which for 0.01 and no momentum was scheduled via callbacks in Keras support. Pearson's Phi coefficient was estimated for each input and output parameter, which is presented in Figure 4. Pearson's Phi coefficient is a measure of association between two nominal variables. It ranges from −1 to 1 and provides the strength and direction of the relationship between the two variables. A value of 1 indicates a strong positive association, a value of −1 indicates a strong negative association, and a value of 0 indicates no association. Pearson's Phi is commonly used in contingency table analysis [78].

Figures 5 and 6 provide the scatterplots and statistical analysis for normalization for input data used in this study, which is included H, β, γ, c', ϕ', V parameters. A scatterplot is a type of data visualization that displays the relationship between two variables [79], which normally input parameters for a specific type of analysis. It consists of points plotted on a two-dimensional plane, where each point represents the value of one variable relative to the other [78]. Scatterplots are particularly useful for identifying

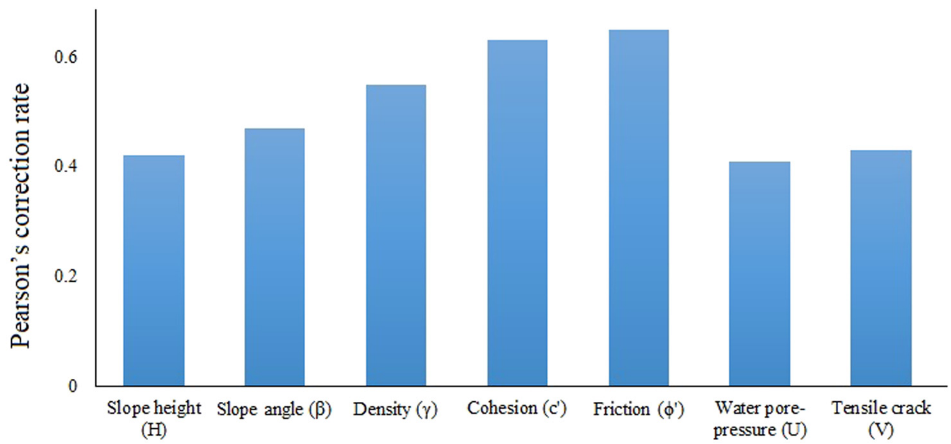

Figure 4: Pearson's coefficient for each factored parameters.

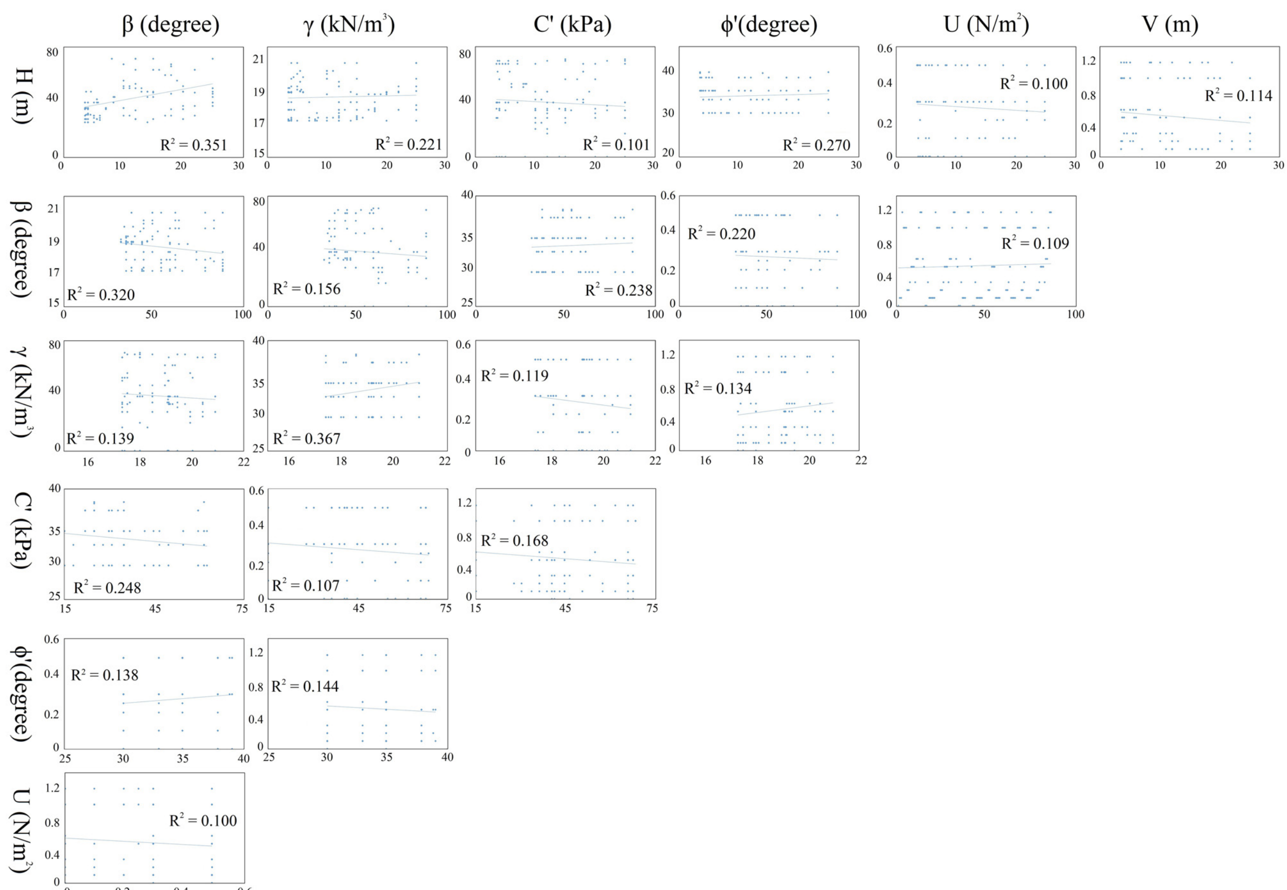

Figure 5: The scatterplot for input data used in this study.

patterns, trends, and potential correlations between variables. For instance, if the points on the plot form a clear pattern, such as a straight line, it suggests a strong relationship between the variables, while a more scattered distribution indicates a weaker relationship or no relationship at all. By visually examining the scatterplot, analysts can gain insights into the nature and strength of the relationship between the variables, helping them

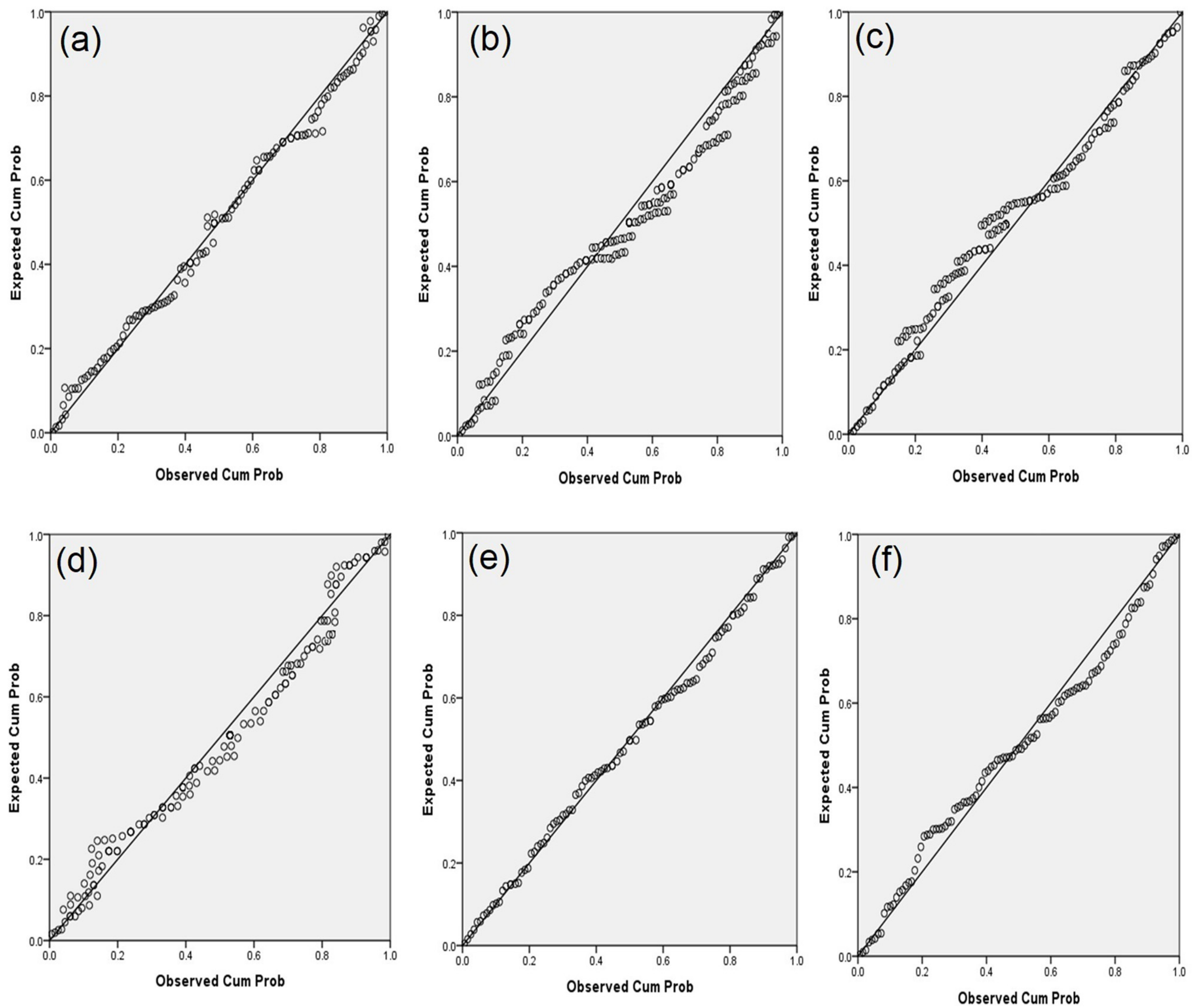

Figure 6: The statistical analysis for normalization of input parameters: (a) H, (b) β, (c) γ, (d) c', (e) ϕ', (f) V.

make informed decisions in the process of modeling [79]. Statistical normalization, in other words, refers to the process of transforming data into a standard format to make it more interpretable or comparable [78]. Normalization techniques are commonly used in data preprocessing to address issues such as varying scales, units, or distributions among different variables. One of the most common normalization techniques is z-score normalization (standardization), where each data point is transformed to have a mean of zero and a standard deviation of one [78]. This method allows analysts to compare variables on a common scale and facilitates the interpretation of statistical measures such as means and standard deviations. Other normalization techniques include min–max scaling, where data is scaled to a fixed range (e.g., between 0 and 1), and robust scaling, which is less sensitive to outliers compared to standardization [79].

2.4 Model validations

To assess the DTR method rigorously, its accuracy was evaluated using statistics from the confusion matrix and statistical error indexes. A confusion matrix is a table used to evaluate the performance of a classification model. It summarizes the true positive, false positive, true negative, and false negative predictions made by the model. The entries in the matrix are used to calculate various evaluation metrics such as accuracy, precision, recall, and $F1$

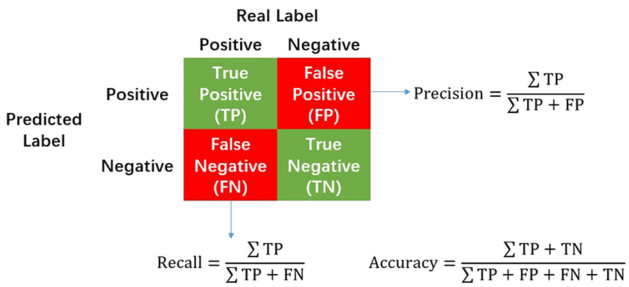

Figure 7: The confusion matrix and evaluation criteria [79].

score, which provide insight into the model's performance and help identify areas for improvement. Confusion matrices are commonly used in fields such as machine learning to provide performance analysis for different learning algorithms [78]. The coordination of the positivity and negativity of the variables, as well as the evaluation criteria estimations in a confusion matrix [79], is presented in Figure 7. In accordance with this figure, the evaluation criteria estimated via the confusion matrix can be calculated as follows:

$$\text{Accuracy} = \frac{\sum \text{TP} + \text{TN}}{\sum \text{TP} + \text{FP} + \text{FN} + \text{TN}}, \tag{1}$$

$$\text{Precision} = \frac{\sum \text{TP}}{\sum \text{TP} + \text{FP}}, \tag{2}$$

$$\text{Recall} = \frac{\sum \text{TP}}{\sum \text{TP} + \text{FN}}. \tag{3}$$

Additionally, the mean absolute error (MAE), MSE, and root-mean-square error (RMSE) were considered as error evaluation indexes, which provide the DTR-based model errors during prediction. MAE is a commonly used metric for evaluating the accuracy of a prediction algorithm. It measures the average of the absolute differences between the predicted values and the actual values. It is defined as MAE = $(1/n) \times \Sigma\,|\,\text{actual} - \text{predicted}\,|$, where n is the number of samples and actual and predicted are the actual and predicted values, respectively. MAE provides a robust measure of prediction accuracy, as it is insensitive to outliers. MSE is a common metric for evaluating the accuracy of a prediction algorithm. It measures the average of the squared differences between the predicted values and the actual values. It is defined as MSE = $(1/n) \times \Sigma(\text{actual} - \text{predicted})^2$. The squared differences amplify larger errors compared to the absolute differences in MAE, making MSE a more sensitive measure of prediction accuracy. RMSE is a commonly used metric for evaluating the accuracy of a prediction algorithm. It is the square root of the mean of the squared differences between the predicted values and the actual values. It is defined as RMSE = √(MSE) = $\sqrt{(1/n) \times \Sigma\,(\text{actual} - \text{predicted})^2}$. RMSE provides a more interpretable measure of prediction accuracy, as it is expressed in the same units as the actual and predicted values. Conversely,

$$\text{MAE} = \frac{1}{n} \times \sum |\text{Actual-Predicted}|, \tag{4}$$

$$\text{MSE} = \frac{1}{n} \times \sum (\text{Actual} - \text{Predicted})^2, \tag{5}$$

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{1}{n} \times \sum (\text{Actual} - \text{Predicted})^2}. \tag{6}$$

3 Results

Based on the methodology previously discussed, this research attempted to use the DTR classification algorithm to investigate rotational failure in earth-slopes and embankments. In this regard, the main factored parameters conclude H, β, γ, c', ϕ', U, and V was considered as input data that directly affected on slope's stability, $F.S$, and SDS are used for prediction modelling by DTR. Results were validated using statistical error indices and a confusion matrix, which are commonly used performance controllers for machine learning algorithms. The modeling results were plotted, and the coefficient of determination (R^2) was estimated for all the predictions in both testing and training datasets. As presented in Table 2, the output of the model was shown as FS, SDS, and stability class for slope, which are discrete quantities. These discrete quantities are adopted and estimated from continuous input quantities, which is consistent with the functional nature of the forecasting algorithm used. This issue will also have a significant impact on increasing the accuracy of model implementation. Figures 8 and 9 provides the predictive model results for both the testing and training databases for estimating FS, SDS, and stability classes. Table 3 illustrates the results of the linear relationship between FS and factored parameters, as predicted by the model-studied slope cases for both testing and training datasets. Also, Table 4 provides information about the model validation process. Figures 10–12 provide model accuracy and errors during the process as well as decision levels that consider calculating stability classes with the DTR algorithm.

Figures 8 and 9 are provide detailed variations of actual FS, SDS, and stability class for earth-slope versus predictive values for both testing and training datasets

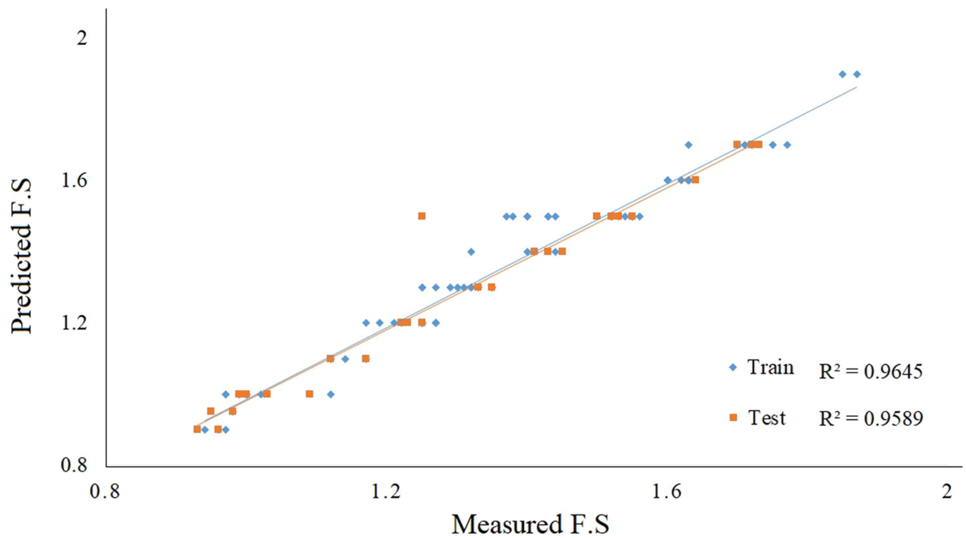

Figure 8: *F.S* variations between actual-predicted values in train and test datasets.

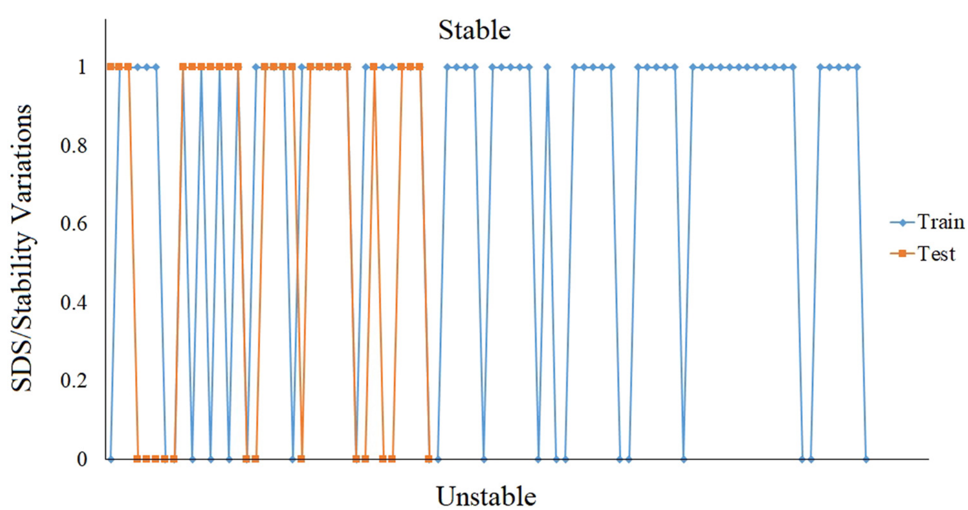

Figure 9: SDS and stability class variations between actual-predicted values in train and test datasets.

Table 3: DTR regression relationships obtained by predictive model

Index	Dataset	Relation
F.S	Train	$F.S = 0.0172\gamma - 0.0392\beta - 0.00428H + 0.085c' + 0.0054\phi' - 0.31U - 0.21V + 0.9452$
	Test	$F.S = 0.0083\gamma - 0.042\beta - 0.0061H + 0.077c' + 0.002\phi' - 0.56U - 0.32V + 1.068$
Stability class/SDS	Train	SC or SDS = 1 (stable) if *F.S* is $x > 1.0001$
	Test	SC or SDS = 0 (unstable) if *F.S* is $x < 1.0000$

which is resulted from main database contained 120 slope cases. The results were measured by the coefficient of determination (R^2) and linear regression to understand the scattering status of the obtained results. The figures show that R^2 values for testing and training datasets are 0.9645 and 0.9589, respectively. R^2 results indicate that the model has good agreements with the prediction of actual data in both testing and training sets.

Table 4: Validation table for prediction process estimated by DTR model

Parameter	Dataset	Confusion matrix			MAE	MSE	RMSE
		Precision	Recall	Accuracy			
F.S	Train	0.9025	0.9025	0.9107	0.1242	0.1722	0.1098
	Test	0.8811	0.8825	0.8711	0.2360	0.2441	0.2209
SDS	Train	0.8629	0.8535	0.8629	0.2571	0.2663	0.2344
	Test	0.8077	0.8044	0.8044	0.2700	0.2736	0.2557
Stability class	Train	0.8956	0.8960	0.8960	0.1925	0.1932	0.1650
	Test	0.8673	0.8649	0.8648	0.2102	0.1988	0.1920

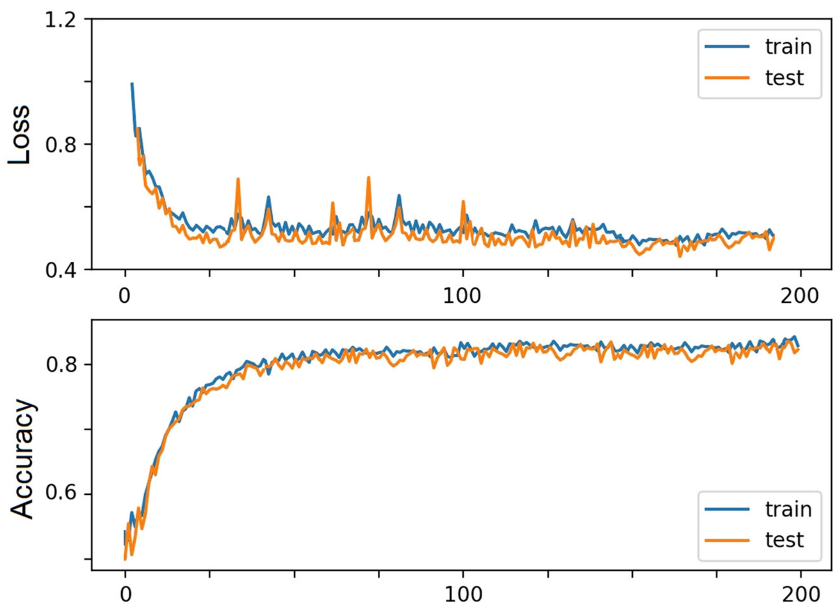

Figure 10: Predictive model loss function and accuracy for training and test dataset.

Table 3 shows the relationship between the DTR prediction model with FS, SDS, and stability class. Slope stability is directly increased by c', ϕ', γ and decreased by β, H, V, U. These factored parameters also show a linear relationship with slope durability and slope classes. Table 3 shows that γ, c', ϕ', have positive effects on FS, while U, V, H and β have negative effects. So, the stabilization process has to be considered based on increases positive partial factors (like enhancing the geo-material propitiates and modifying geometry and reinforce slope mass) by considering all negative parameters (like geometrical modification with efficient drainages). Table 4 presents the estimated confusion matrix and statistical error indexes for the DTR predictive model. The model achieves 90.25% precision and 91.07% accuracy in calculating the FS. The SDS and stability class have 86.29 and 86.29% precision and 89.56 and 89.60% accuracy values, respectively. The FS prediction has MAE, MSE, and RMSE values of 0.1242, 0.1722, and 0.1098, whereas SDS and stability class have values of 0.2571, 0.2663, 0.2344 and 0.1925, 0.1932, 0.1650. These findings demonstrate, from a practical standpoint, that the DTR algorithm is effective and useful for predicting the sfactored-based stability analysis for soil slopes and embankments.

4 Discussion

This article highlights the importance of input factors in affecting the performance of DTR models. . Some key parameters are:

- *Maximum tree depth*: Controls the size of the tree and limits the number of splits in the tree, which affects the

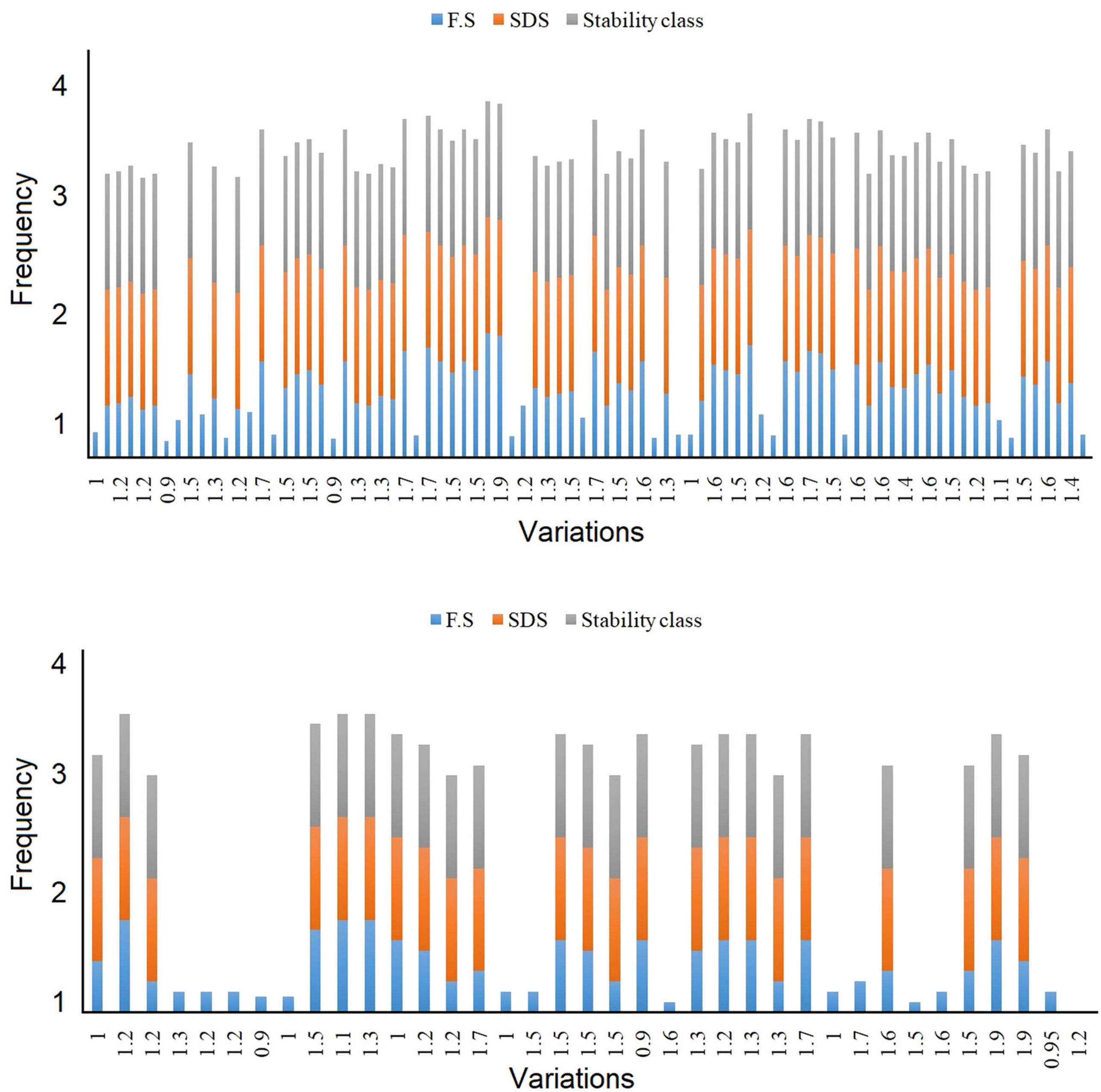

Figure 11: The SDS, *F.S* and stability class variations for test-train datasets based on decision frequency.

model's ability to capture complex relationships between features and the target.

- *Minimum samples per leaf node*: Specifies the minimum number of samples required to form a leaf node, which affects the model's ability to generalize to new data.
- *Splitting criterion*: Determines how the model selects the best feature to split on at each node, such as MSE or MAE.
- *Maximum number of features to consider when splitting*: Controls the number of features considered when making a split, which can help reduce overfitting by limiting the model's ability to memorize the training data.
- *Regularization*: This parameter controls the complexity of the tree by adding penalties to the cost function that the model is trying to minimize. Common regularization techniques include L1 (Lasso) and L2 (Ridge) penalties.
- *Pruning*: This technique involves removing branches of the tree that do not contribute much to the overall performance of the model. Pruning helps to reduce overfitting and improve the interpretability of the model.

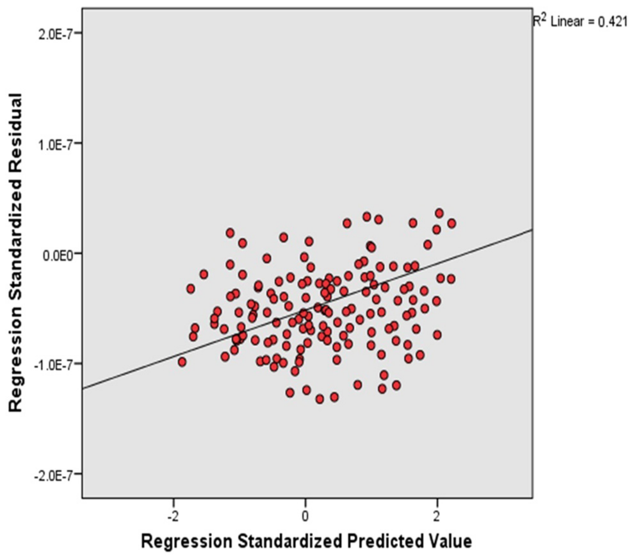

Figure 12: The results statistical normalization for predict and calculated *F.S* values.

- *Random seed*: Specifying a random seed value for the model can ensure that the same results are obtained each time the model is trained, even with the same data and parameters.
- The results from the DTR model showed high accuracy and precision in predicting the FS, SDS, and stability class for slopes and embankments. The model's R^2 values (0.9645 for testing and 0.9589 for training datasets) indicate a strong correlation between the predicted and actual values, suggesting that the model is reliable for practical applications. The influence of the parameters on slope stability was consistent with geotechnical principles: parameters like cohesion (c'), internal friction angle (ϕ'), and unit weight (γ) positively impacted the FS, while height (H), slope angle (β), pore-water pressure (U), and surcharge (V) negatively impacted it. This aligns with the understanding that improving soil strength and reducing destabilizing forces enhances slope stability.
- Proper tuning of these parameters can result in better model performance, improved accuracy, and reduced overfitting. So, it is important to keep in mind that overfitting is a common problem in regression trees and can be mitigated by carefully choosing the input parameters, as well as by using cross-validation to evaluate the performance of the model on unseen data. Additionally, it is a good practice to compare the performance of multiple models with different input parameters to find the best-performing model. Even though the DTR model performed well in the prediction of slope stability conditions, overfitting has to be considered each time using DTR. Generally, regression trees are prone to overfitting, which means that the model becomes too complex and fits the training data too well, resulting in poor generalization to new data. Overfitting occurs when the tree has too many splits and becomes too deep, leading to a model that is too complex to effectively capture the underlying patterns in the data. To combat overfitting in DTR, there are several techniques that can be used such as pruning, regularization, cross-validation, and feature selections. The presented study used cross-validation, pruning, and regularization techniques to reduce the overfitting in the learning procedure of the model.

In comparing these findings with previous research, it is essential to highlight both the similarities and differences (e.g., [80–89]):

- *Accuracy and Model Performance*: The precision and accuracy of the DTR model (over 90% for FS and around 86% for SDS and stability class) are comparable to or even exceed those reported in previous studies using different machine learning models, such as support vector machines (SVM) or neural networks, which typically report accuracy in the range of 80–90%.
- *Parameter Influence*: Previous studies also consistently report the positive impact of cohesion (c'), internal friction angle (ϕ'), and unit weight (γ) on slope stability, and the negative impact of factors like slope height (H) and slope angle (β). However, the DTR model's ability to explicitly show the linear relationships between these factors and stability indicators enhances interpretability, which might not be as clear in more complex models like neural networks.
- *Model Validation Metrics*: The use of MAE, MSE, and RMSE for validation is standard in the field. The relatively low error values in this study suggest that the DTR model is particularly well-suited for this type of prediction, potentially offering an advantage over more computationally intensive methods like deep learning, which may require larger datasets and more computational resources.
- *Practical Implications*: The practical utility of the DTR model, given its balance of accuracy and interpretability, may surpass that of more complex models, particularly in engineering applications where understanding the influence of specific parameters is crucial. This can lead to better-informed decisions in slope stabilization efforts.

As compared to selected studies, the DTR model not only aligns with findings from previous studies but also offers clear advantages in terms of accuracy, interpretability, and practical applicability. Future research could explore combining DTR with other models or hybrid approaches to further enhance prediction accuracy and broaden the model's applicability to different types of slopes and geotechnical conditions.

5 Conclusion

This study introduces an advanced predictive model that utilizes data mining and complex DTR algorithms to assess slope stability based on a comprehensive database of 120 slope cases from Iran. The model demonstrates significant effectiveness, achieving an accuracy of 91.07% and a precision of 90.25% for predicting the FS. For SDS, the model's accuracy is 86.29%, and it performs with an accuracy range of 89.56–89.60% for stability class predictions. The model's performance is further validated by error metrics, with MAE, MSE, and RMSE values indicating robust prediction capabilities. A notable finding of this study is the substantial impact of parameters such as cohesion (c'), friction (ϕ'), and density (γ) on slope stability, where increased values enhance stability. Conversely, higher slope angle (β), height (H), tensile crack (V), and water pore-pressure (U) are found to negatively influence stability. This insight provides a clear understanding of how various factors interact to affect slope stability. To maximize the utility of the DTR model, it is recommended that it be applied in real-world slope stability assessments, especially in regions with geological conditions similar to those of the Iranian slopes studied. Future research should focus on adapting the model to different geographical locations and soil types to enhance its generalizability. Additionally, integrating real-time monitoring data could further improve the model's accuracy and responsiveness. However, the study acknowledges certain limitations. The model is based on a specific dataset from Iran, which may restrict its applicability to other regions with different environmental and geological conditions. Additionally, the model's effectiveness depends on the accuracy of input parameters and may not account for all variables affecting slope stability. Ongoing refinement and validation with diverse datasets are crucial to address these limitations and fully exploit the model's potential across various contexts.

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