ZKG INTERNATIONAL
ISSN / eISSN 2366-1313
Publisher BAUVERLAG BV GMBH,
AVENWEDDER STR 55, GUTERSLOH,
GERMANY, 33311
Volume 25-Issue 1-(2025)
https://doi.org/10.63386/620241

Predicting Slope Stability Using Tree-Based Classifiers: Comparative Study of J48 and Random Tree Methods

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Revised: May 22, 2025; **Accepted:** May 23, 2025; **Published**: May 23, 2025

Abstract

The assessment of slope stability constitutes an essential to geotechnical analysis and geological research due to the catastrophic consequences associated with slope failures in many countries. This research focuses upon the development of new decision tree models, namely Random Tree and J48, for predicting slope stability. The models were constructed and validated using a dataset consisting about 107 slope stability case histories. This dataset includes six key parameters: unit weight, cohesion, angle of internal friction, slope angle, slope height, and pore water ratio, all of which are essential for assessing slope stability. The efficient functioning of the recommended models is assessed using performance measures, including the accuracy (ACC), Matthews's correlation coefficient (MCC), precision, recall, and F-measure. The Random Tree classifier achieved superior predictive performance on the slope stability dataset, attaining an accuracy of 95.33% across both training and test phases, which surpasses the J48 model (86.92%) and other recently proposed models, as evidenced by comparative metrics including MCC, precision, recall, and F-measure.

Keywords: Random tree; J48; slope stability prediction; confusion matrix.

1. Introduction

The precise prediction of slope stability, which has grown to be a major problem across the globe, is essential to geotechnical engineering. Slope instability, along with earthquakes and volcanoes, has emerged as a highly significant geological catastrophe on a global scale. Slope stability must be attained in order to reduce or eliminate the damaging impacts of landslides. However, due to the complex nature of slope structures and the severity in gathering essential input data related to important geotechnical parameters, it is difficult to effectively estimate slope stability [1-3].

Numerical and analytical methods have been widely adopted to simulate slope-related failure mechanisms, including submarine landslides, soil-structure interactions, and tunnel stability [4-7]. Studies focusing on experimental and field-based observations have enhanced understanding of slope deformation under varying geotechnical and hydrological conditions [8-11]. The integration of remote sensing, deformation monitoring, and support systems has improved predictive accuracy and risk management in slope and underground excavation scenarios [12-14]. Furthermore, broader investigations into fluid–soil interactions, flood impacts, and rainfall-induced instabilities contribute significantly to the slope stability knowledge base and hazard mitigation strategies [15, 16].

Numerous techniques have been proposed to evaluate slope stability, using limit equilibrium methods [17, 18] and numerical modelling (e.g., finite element method) [19-21] being the most frequently used [22, 23]. Empirical equations [24, 25] and limit analysis approaches based on lower and upper bound theorems [26] are other methods. However, each of the aforementioned strategies has drawbacks. For instance, the true stress levels on the slip surfaces cannot be captured by limit equilibrium techniques [27], and since they are simplified, assumptions lose some of their validity. [1]. The time-consuming numerical methods depend significantly on the precise estimation of the physical and geotechnical parameters for their reliability.

Computing techniques like Artificial Neural Networks (ANNs) and Support Vector Machines (SVM) have lately acquired prominence for estimating slope stability. [23, 28, 29]. A summary of prior research on using soft computing techniques to forecast slope stability is shown in Table 1. The ANN and SVM have become incredibly prominent among these techniques. The appeal of ANN and SVM stems from their capacity for flexible nonlinear modelling and their ability to function without the requirement for pre-existing knowledge regarding a specific model structure [30]. Additionally, they outperform conventional analytical and regression techniques for estimating slope stability [31, 32]. Table 1 illustrates that past research studies have primarily categorized the factor of safety (FOS) for slope stability under static conditions, employing key parameters such as slope angle (β), cohesion (c), unit weight (γ), height (H), and angle of internal friction (φ). However, the accuracy of these predictive models is not adequately interpreted and falls short of fully addressing the challenges associated with slope stability estimation. As a result, the problem of predicting slope stability remains a significant challenge, prompting further exploration in this field. Any enhancement to existing methods for slope stability prediction is considered a valuable contribution. Therefore, it is crucial to emphasize the need for more systematic and comprehensive research to advance the prediction of slope stability.

Table 1. Previous research on slope stability prediction using soft computing approaches.

Model	**Data size**	**Source**
FFNN	82	Feng [33]
BPNN	32	Lu and Rosenbaum [34]
ANN and ANFIS	59	Li [35]
CNN	64	Huang *et al.* [36]
BPNN	46	Sakellariou and Ferentinou [1]
BPNN	27	Wang *et al.* [37]
SVM	46	Samui [38]
SVM	10	Zhao [39]
ANN	36	Choobbasti *et al.* [40]
ANN	46	Das *et al.* [41]
ANN	675	Erzin and Cetin [31]
ELM	97	Liu *et al.* [22]
PSO–ANN	699	Gordan *et al.* [28]
LS-SVC	168	Hoang and Pham [42]
FNs, MARS, MGGP	103	Suman *et al.* [3]
FEM-ANN	100	Verma *et al.* [43]
PSO–ANN	83	Rukhaiyar *et al.* [44]
PSO–LSSVM	46	Xue [23]
NBC	82	Feng *et al.* [45]
GBM	221	Zhou *et al.* [46]
TAN	87	Ahmad *et al.* [47]
DT, RF, AdaBoost	700	Asteris *et al.* [48]

Note: AdaBoost: Adaptive boosting, ANN : Artificial Neural Networks, ANFIS: adaptive neuro-fuzzy inference system, CNN: Chaotic Neural Network, DT: Decision tree, ELM: Extreme learning machine, TAN: Tree augmented Naive-Bayes classifier, FNs: Functional networks, PSO: Particle swarm optimization, RF: Random forest, LSSVM: least squares support vector machine, SVM: support vector machine, NBC: Naive-Bayes classifier, MGGP: Multigene genetic programming, MARS: multivariate adaptive regression splines, FFNN: Feed forward Neural Network, BPNN: Back-Propagation Neural Network, GBM: Gradient boosting machine, LS-SVC: Least Squares Support Vector

The main objectives of this study are to develop decision tree models that can accurately predict slope stability by capturing the complex relationship between the factors that influence slope stability and to evaluate the performance of the proposed models by comparing them to other widely used computing models discussed in the literature.

This paper's outline can be summed up as follows: The methodology will be described in Section 2, Additionally, developing the prediction models is explained in Section 3. The results and discussions are compiled in Section 4 and the last Section set out the conclusions and future prospect of this study.

2. Methodology

2.1 Dataset

In the current study, 107 slope stability data were collected from Sah et al., [49], Lu and Rosenbaum, [34], and Li and Wang, [50] to developed and validate the proposed models. Table 2 provides an overview of the dataset inputs and outputs used in this study using key variables such unit weight (γ), cohesion (c), angle of internal friction (φ), slope angle (β), slope height (H), and pore water ratio (r_u).

Table 2. Inputs and output of the present study.

γ (kN/m^3)	c (kPa)	φ (°)	β (°)	H (m)	r_u	Stability Status
18.8	14.4	25.02	19.98	30.6	0	Stable
18.77	30.01	9.99	25.02	50	0.1	Stable
19.97	19.96	36	4550	50	0.5	Failed
...	...	...	...	...	...	...
...	...	...	...	...	...	...

γ (kN/m^3)	c (kPa)	φ (°)	β (°)	H (m)	r_u	Stability Status
...	...	...	...	...	...	...
26.43	50	26.6	40	92.2	0.15	Stable
26.7	50	26.6	50	170	0.25	Stable
26.8	60	28.8	59	108	0.25	Stable

Correlation analysis was used to evaluate the correlation ($\boldsymbol{\rho}$) between different parameter as shown in Table 3. It is represented as follow:

$$\rho(p,q)=\frac{\mathrm{cov}(p,q)}{\sigma_p\sigma_q} \tag{1}$$

where "cov" represents covariance, σ_p indicates the standard deviation of "*p*" while σ_q reparents the standard deviation of "*q*". The relationship between the "*p*" and "*q*" parameters is especially strong when the value of $\boldsymbol{\rho}$ is greater than 0.8. Values less than 0.3 imply a tenuous and weak relationship between the "*p*" and "*q*" parameters, whereas values ranging from 0.3 to 0.8 indicate an intermediate relationship [51]. Its value is considered to be a "strong correlation" if it is higher than 0.8 [52]. According to Table 3, the most significant possible absolute correlation coefficient is 0.523.

Table 3. Inputs and output of the present study.

	γ (kN/m^3)	c (kPa)	φ (°)	β (°)	H (m)	r_u
γ (kN/m^3)	1					
c (kPa)	0.523	1				
φ (°)	0.448	0.326	1			
β (°)	-0.003	-0.016	0.096	1		
H (m)	0.500	0.488	0.263	0.007	1	
r_u	0.011	-0.100	0.073	0.162	-0.187	1

2.2 Decision Tree (DT)

The DT model is a foundational machine learning classification technique that predicts the value of a target variable by learning straightforward decision rules from data features. The algorithm's implementation method also involves DT generation, DT pruning, and feature selection. The algorithm first categorizes based on the traits before recursively creating the DT. In addition, it prunes the resulting DT to remove any unnecessary or superfluous branches. The model's local optimal solution is represented by the production of the DT, and the global optimal solution is represented by the pruning of the DT. The DT is applied in the actual slope prediction and is intuitively comprehended.

2.2.1 Random Tree

Leo Breiman and Adele Cutler were the ones who first suggested random trees. Both regression and classification tasks can be handled by the algorithm. [53, 54]. The decision tree utilized in this research is developed using a stochastic process. To create a random dataset for building the decision tree, it utilizes the idea of bagging. Each node in the conventional tree is divided according to the optimal division of all attributes. Moreover, in the random tree model, each node is split using the best split from a randomly selected subset of attributes. Additionally, the random tree model allows for the estimation of class probabilities. This approach is implemented to maximize the accuracy of the classifier parameters, including the minimum number of instances and the *K*-value represents the number of sets used for randomly selecting attributes

2.2.2 J48

Quinlan proposed the commercial version 4.5 (C4.5) algorithm, and J48 is an open-source of Java implementation of this algorithm on the WEKA data-mining platform [55], is an established machine learning technique that is mostly used to build decision trees. The method uses an entropy-based metric as the selection criterion, which quickly yields a sufficient classification accuracy. Utilizing the divide-and-conquer strategy, it is a modified version of the ID3 algorithm [55]. The pruning approach and the method's more effective management of numerical attributes, missing values, and noisy data are its key improvements. The creation of the decision tree and the creation of the rules (structure and design) usually constitute the two steps that make up the C4.5 algorithm. After calculating the most significant character attribute for information gain, the entropy is evaluated. The entropy formula is displayed here, where S stands for entropy and p represents a class proportion in the output.

$$Entropy(S) = \sum_{i=1}^{n} -p_i \times \log_2 p_i \tag{2}$$

Furthermore, according to Equation 2 for Gain (S, A), where S is a case set, A is a case attribute, $|Si|$ is the number of cases to i, and $|S|$ is the number of cases in the set, the attribute with the highest gain value is chosen as the root attribute.

$$Gain\left(S,A\right)=Entropy\left(S\right)\sum_{i=1}^{n}\frac{|S_i|}{|S|}\times Entropy\left(S\right) \quad (3)$$

The C4.5 method produces a DT by combining the top-down and recursive-splitting strategies. The tree structure of C4.5 has a root node, internal nodes, and leaf nodes. The root node holds all of the input data. While the leaf node denotes the result obtained from the provided input parameters, an internal node within the decision tree often exhibits two or more branches along with a decision function.

2.3 Performance Evaluation

The performance of the trained slope stability models was predicted using a number of statistical classification assessment criteria, including counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The confusion matrix follows the conventional format, where P and N refer to actual positive and negative instances, respectively. Figure 1 shows the confusion matrix as a result of adding the counts.

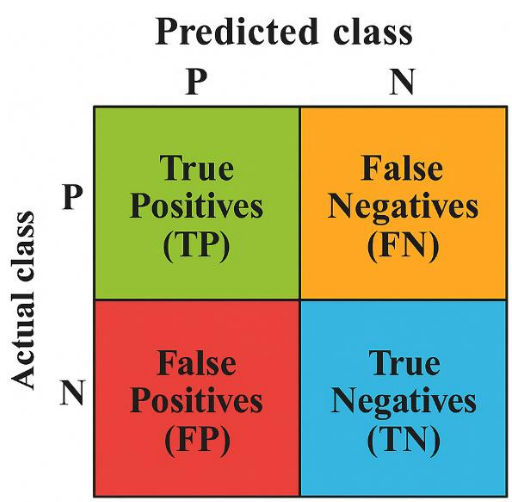


Figure 1. Confusion matrix for the binary class problem.

Assuming that the slope's stability is considered a positive outcome, True Positive (TP) and True Negative (TN) shows the correctly predicted instances of stability and failure, respectively. On the other hand, False Negative (FN) and False Positive (FP) occur when the predictions incorrectly identify instances as negative or positive. The models' prediction performance was evaluated by comparing these outcomes obtained from the confusion matrix using the classification evaluation metrics given below [56-58]:

$$ACC = \frac{TN + TP}{TN + FP + FN + TP} \tag{4}$$

$$MCC = \frac{TN \times TP - FP \times FN}{\sqrt{(FN + TP)(FP + TN)(FP + TP)(FN + TN)}} \tag{5}$$

$$Precision = \frac{TN}{FN + TN} \, or \, \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TN}{TN + FP} \, or \, \frac{TP}{TP + FN} \tag{7}$$

$$F - measure = \frac{1}{Precision} + \frac{1}{Recall} \tag{8}$$

Accuracy (ACC) is basically the addition of *TP* and *TN*, and it displays the percentage of instances in the data that are effectively classified. This evaluation metric evaluates the overall correctness of the model's predictions. However, caution should be exercised when interpreting the accuracy measure in cases where the data is unevenly distributed. This is particularly relevant when the majority of class predictions for failed pillars are positive, which can lead to a misleadingly high accuracy score. Consequently, in this study, additional evaluation measures like as precision, recall, F-measure, and Matthews's correlation coefficient (MCC) were used to further assess the model's performance. The true positive rate has been used to describe recall, whereas precision is known as the positive predicted value; The *F*-measure is a broad index that ranges from 0 (the worst value) to 1 (the highest value) and examines the both recall and precision performance [58]. The MCC quantifies the correlation amongst the observed and predicted classes of failed and stable cases [45]. It is a widely used metric in statistical analysis, ranging from -1 to 1. MCC value of "-1" indicates complete disagreement (strong negative association), "1" represents complete agreement (strong positive association), and "0" signifies no significant correlation between the prediction and the ground truth (very weak or no correlation between the dependent and independent variables).

3. Development of Prediction Models

This paper employed the J48 and random tree algorithms to construct models for the slope stability determination. The input variables consisted of slope height (H), cohesion (c), angle of internal friction (φ), slope angle (β), unit weight (γ), and pore water ratio (r_u), while the dependent variable was slope stability. To calculate the predictive performance of the machine learning (ML) algorithms on the given database, the train-and-test approach was adopted, which is a commonly used technique. Figure 2 illustrates the systematic procedure for estimating slope stability using the proposed models.

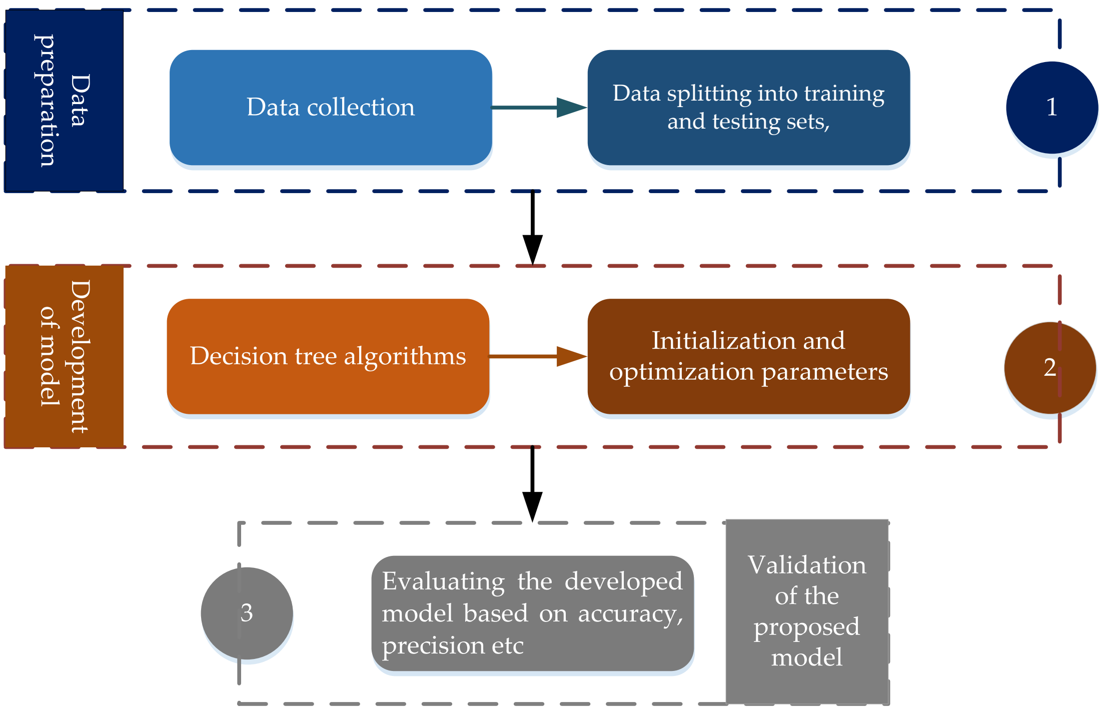
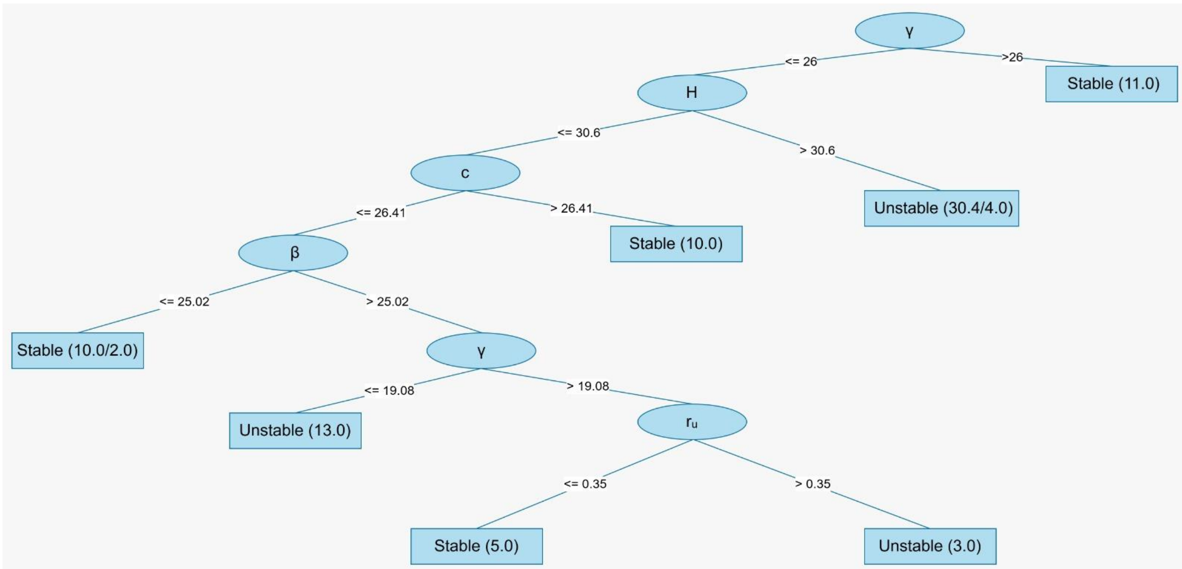
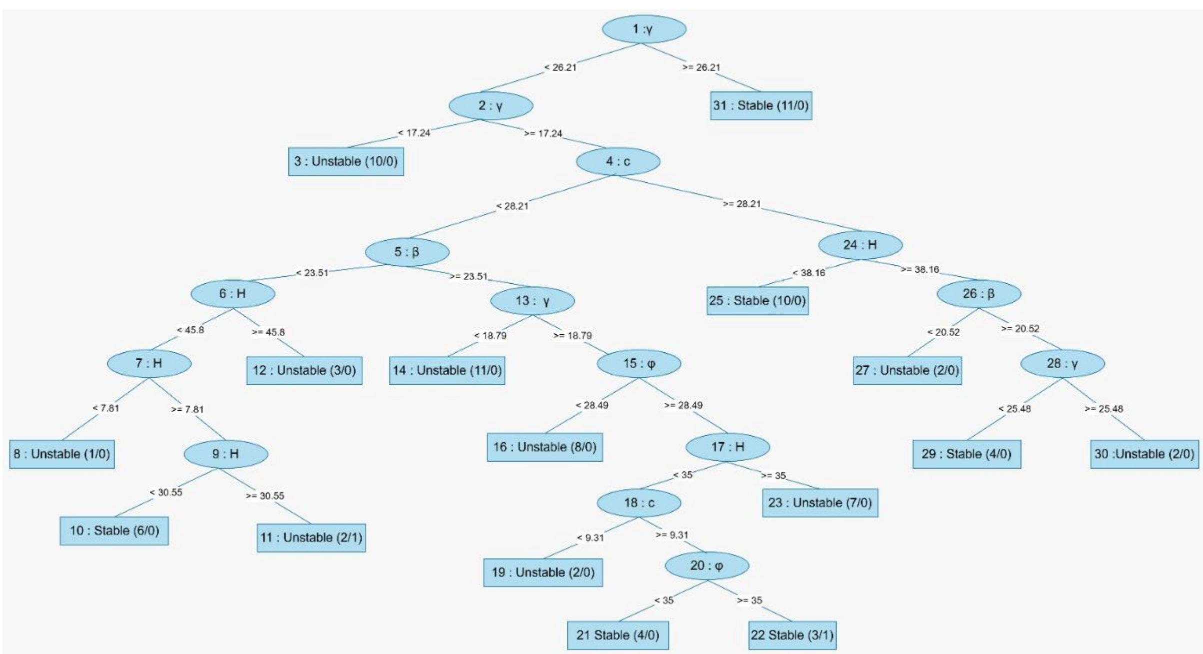


Figure 2. Working procedure for the prediction of slope stability using random tree and J48.

Using the Waikato Environment for Knowledge Analysis (WEKA) application, the J48 and random tree algorithms were implemented to create the suggested models. To train the models, the training dataset was put into WEKA in attribute relation file format. After training, an additional testing dataset that was obtained from the initial training dataset was used to test the models. The ideal settings for the J48 model parameters, such as the confidence factor and the minimum number of instances per leaf, were established through a trial-and-error process in order to achieve the most effective classification accuracy. The minimal instances per leaf were discovered to be 5, while the ideal confidence factor for the J48 method was determined to be 0.25. Similar results were reported for the random tree technique, where the minimal instances per leaf were discovered to be 2 (refer to Figure 2) and the optimal value for *K* was found to be 3.



(a)



(b)

Figure 2. (a) Random tree and (b) J48

4. Results and Discussion

Using the identical training and testing datasets, the performance results of the random tree and J48 models were obtained and compared. Table 4 shows the corresponding confusion matrix for each model that was identified.

Table 4. The outcomes of the confusion matrices for both the training and testing datasets

Dataset	Actual	Random tree		J48	
		Predicted			
		Stable	Failed	Stable	Failed
Training	Stable	37	1	38	0
	Failed	1	47	11	37
Testing	Stable	6	3	8	1
	Failed	0	12	2	10

The number of cases that were successfully predicted is represented by the values on the confusion matrix's major diagonal. In the training dataset total 84 cases are successfully classified and 18 cases are correctly identified in the testing dataset, it is evident from the findings shown in Table 4, that the sizable fractions of the cases were correctly classified. Equations (3) – (7) were used to determine performance metrics such ACC, MCC, precision, recall, and F-measure using data from Table 4, as shown in Table 5. The performance comparison between the Random Tree (RT) and J48 models shows that RT achieved higher training accuracy (97.67%) and MCC (0.953), indicating strong fitting and excellent classification of both stable and failed slopes. While both models showed similar testing accuracy (85.71%), the RT model demonstrated superior performance in identifying failed slopes, achieving perfect recall (1.000), which is critical for slope stability assessments where overlooking failures can have serious consequences. Although J48 offered more balanced metrics across both classes, the RT model's higher sensitivity to failure cases and overall stronger predictive power make it a more reliable choice for slope stability prediction tasks. The random tree model demonstrates favorable performance when training and testing the slope stability datasets, as evidenced by the results obtained. In comparison, the J48 model exhibits lower ACC and MCC in the training and testing datasets (see Figure 3).

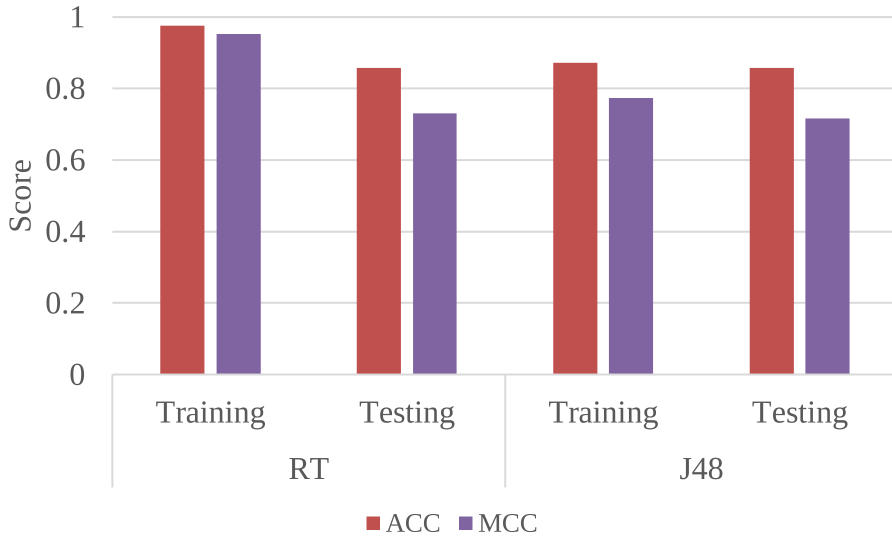


Figure 3. Comparison of the performance metrics of developed models.

Both the random tree and J48 models are considered white-box models, which means they are more intuitive and interpretable compared to other models. When assessing the overall prediction performance by considering metrics such as ACC, Recall, Precision, F-measure, and MCC, a comprehensive analysis reveals that the J48 model demonstrates relatively better performance compared to the random tree model. The dataset exhibits a relatively unbalanced distribution and is of small size. In general, when dealing with limited datasets, it can affect the model's ability to generalize and its overall reliability. Although the random tree and J48 algorithms demonstrate good performance with limited datasets, their predictive capabilities could potentially improve when applied to larger datasets. It is vital to identify that the developed models can be modified and refined over time as new data becomes available, allowing for continuous improvement and the potential for improved results. The generated models can always be modified to increase their performance and produce better outcomes when new information becomes available. Additionally, it is crucial to acknowledge that the dataset is unbalanced, with a higher number of failed cases (60) compared to stable cases (47). Therefore, it is imperative to establish a larger and more balanced slope stability database. It should be noted that other variables could also affect the prediction outcomes. Factors such as the depth of rocks, soil type, and rainfall can all be taken into consideration when refining these models. Whereas, the six factors utilized in the current study partially capture the fundamental conditions for slope stability, it is vital to analyze the influence of additional factors on the prediction results.

Table 5. The results of the developed random tree and J48 models are compared

Model	Dataset	ACC (%)	MCC	Stable			Failed		
				Precision	Recall	F-measure	Precision	Recall	F-measure
RT	Training	97.674	0.953	0.974	0.974	0.974	0.979	0.979	0.974
	Testing	85.714	0.730	1.000	0.667	0.800	0.800	1.000	0.889
J48	Training	87.209	0.773	0.776	1.000	0.874	1.000	0.771	0.874
	Testing	85.714	0.716	0.800	0.889	0.842	0.862	0.833	0.870

5. Model comparison with recently developed soft computing models

Finally, by comparing the developed tree-based classification models with recently developed soft computing/data mining models that were published in the literature, the accuracy of the models was assessed. The results after comparison are presented in Table 6. It is evident that the prediction accuracies of the proposed models are on par with those achieved by the reported techniques. One significant benefit of the proposed models is their "white box" nature, which explicitly exemplifies the relationship between input and output parameters. This enables users, particularly geotechnical engineers, to efficiently analyze and predict slope stability using these models.

Table 6. Comparison of the test set's performance evaluation

Model	Actual	Predicted		ACC (%)	MCC	Precision	Recall	F-measure	Reference
		Stable	Failed						
SVM	Stable	21	1	73.1	0.541	0.618	0.955	0.750	Zhou et al. [46]
	Failed	13	17			0.944	0.567	0.708	
ANN	Stable	21	1	82.7	0.684	0.724	0.955	0.824	
	Failed	8	22			0.957	0.733	0.830	
RF	Stable	21	1	80.8	0.655	0.700	0.955	0.808	
	Failed	9	21			0.955	0.700	0.808	
SVM	Stable	4	5	66.7	0.372	0.800	0.444	0.571	Lin et al. [59]
	Failed	1	8			0.615	0.889	0.727	
NB	Stable	3	6	55.6	0.124	0.600	0.333	0.429	
	Failed	2	7			0.538	0.778	0.636	

Note. SVM: Support vector machine, ANN: Artificial neural network, RF: Random forest, NB: Naive bayes.

6. Conclusions and Future Prospect

This paper employed the random tree and J48 models to forecast slope stability. These models were trained and tested using slope stability case histories gathered from the literature. The developed models utilize critical input variables, including slope height (H), cohesion (c), angle of internal friction (φ), slope angle (β), unit weight (γ), and pore water ratio (r_u), to predict slope stability. The key findings of this study are outlined below:

1. The total classification accuracy of the random tree model is 95.33% (across both training and test phases), while the J48 model achieves an accuracy of 86.92%. These high accuracies demonstrate the efficiency and reliability of both models for practical applications. The proposed models, in contrast to many soft computing techniques, are simple to use and do not require substantial training. The relationship between the input and output variables is made obvious and readily apparent by them. The study's findings show that the correlations are in good agreement with engineering intuitions and judgements.
2. The performance comparison between the developed models revealed that the random tree model outperformed the J48 model in terms of delivering more accurate and reliable predictions.
3. It is apparent that the presented models could be improved in the future, and the addition of more data will improve their ability for prediction.

In order to assess the reliability of the models in predicting slope stability, future research should employ a more balanced slope stability database. This can be achieved by incorporating additional factors such as rock depth, soil type, and rainfall.

Notation

AdaBoost	Adaptive boosting
ANN	Artificial Neural Networks
ANFIS	adaptive neuro-fuzzy inference system
CNN	Chaotic Neural Network

DT	Decision tree
ELM	Extreme learning machine
TAN	Tree augmented Naive-Bayes classifier
FNs	Functional networks
PSO	Particle swarm optimization
RF	Random forest
LSSVM	least squares support vector machine
SVM	support vector machine
NBC	Naive-Bayes classifier
MGGP	Multigene genetic programming
MARS	multivariate adaptive regression splines
FFNN	Feed forward Neural Network
FoS	Factor of safety
BPNN	Back-Propagation Neural Network
GBM	Gradient boosting machine
LS-SVC	Least Squares Support Vector
H	slope height
c	cohesion
φ	angle of internal friction
γ	unit weight
β	slope angle
r_u	pore water ratio

Conflicts of Interest: The authors declare no conflict of interest.

Data Availability Statement: The data used to support the findings of this study are openly available.

Acknowledgement: The authors would like to acknowledge the Deanship of Graduate Studies and Scientific Research, Taif University for funding this work.

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