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Application of Machine Learning Techniques in Slope Stability Analysis: A Comprehensive Overview

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Abstract

The mining industry needs to accept new-age autonomous technologies and intelligent systems to stay up with the modernization of technology, to benefit the shake of investors and stakeholders, and most significantly, for the nation, and to protect health and safety. An essential part of geo-technical engineering is doing slope stability analysis to determine the likelihood of slope failure and how to prevent it. A reliable, cost-effective, and generally applicable technique for evaluating slope stability is urgently needed. Numerous research studies have been conducted, each employing a unique strategy. An alternate method that uses machine learning (ML) techniques is to study the relationship between stability conditions and slope characteristics by analyzing the data collected from slope monitoring and testing. This paper is an attempt by the authors to comprehensively review the literature on using the ML techniques in slope stability analysis. It was found that most researchers relied on data-driven approaches with limited input variables, and it was also verified that the ML techniques could be utilized effectively to predict slope failure analysis. SVM and RF were the most popular types of ML models being used. RMSE and AUC were used extensively in assessing the performance of the ML models.

1. Introduction

Analyzing the likelihood of slope failures and the results of such failures is an integral part of geo-technical engineering [1-4]. The complexity and uncertainty of the slope conditions, the assumptions and simplifications in the analysis models, and the computational cost and time needed for the analysis are often the limitations of conventional techniques of slope stability analysis [5, 6].

As a branch of artificial intelligence, machine learning offers an alternative approach to slope stability analysis, as it can learn from data and make predictions without explicit rules or equations. In slope stability analysis, the machine learning methods fall into two broad areas: data-driven methods and hybrid methods. Data-driven methods use ML algorithms to directly predict the slope stability parameters or factors of safety from the input parameters such as soil properties, slope geometry, and groundwater level. Hybrid methods combine machine learning algorithms with conventional methods such as limit equilibrium methods (LEMs) or finite element methods to improve the accuracy and efficiency of the analysis.

The factor of safety (FOS) is a typical indicator of slope stability [7], and it may be predicted using ML algorithms based on several input characteristics. The significance and sensitivity of various input variables can be analyzed with the ML methods for slope stability prediction. Slope stability may be quickly assessed and predicted using machine learning algorithms. However, they also need cautious model selection, validation, and interpretation. Several metrics including R^2, mean absolute error (MAE), mean square error (MSE), accuracy, precision, recall, and F1-score can be used to assess and compare the performance and

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reliability of various ML algorithms for slope stability analysis. The findings demonstrate that some machine learning approaches may reliably and accurately predict slope stability, while others may have drawbacks and limitations [8-11].

In India, the use of machine learning for slope stability analysis is still in its infancy due to a need for more relevant research and data. The researchers have tried to predict the factor of safety or the probability of slope failure in different regions and conditions using machine learning techniques, such as support vector machines, decision trees, random forests, and gradient boosting [11, 12, 8]. Outside India, where studies and data were available, machine learning applications in slope stability analysis were more developed and ubiquitous [13-18].

In view of this, the present work involved a comprehensive review of the literature published during 2015-2023 on the use of ML to predict slope failure. Research directions, models, and evaluation methods for machine learning in this domain were subsequently discussed in the study.

2. Literature Review

A systematic literature review (sometimes called a systematic review) helps researchers find, evaluate, and understand all the studies conducted on a specific topic, question or phenomenon.

The purpose of this review is to offer answers to questions raised by previous studies.

First categorizing research topics established the purpose and ultimate goals of this study. Next, the authors established criteria for selecting relevant studies from the search results and implemented the search strategy to collect relevant research papers. The next step was determining if the articles' abstracts and results were relevant to the current study. After that, the necessary information was collected and organized using proper data extraction.

- Research Question 1: Specifically, how is ML being applied to slope stability analysis, how often is it being published, and what are the current trends in the field?
- Research Question 2: How frequently and in what settings did you apply the various machine learning models for slope stability analysis?
- Research Question 3: What data or metrics did you use to evaluate ML models?

The first question was meant to outline developments in slope stability-related ML studies. The publication status of annual studies and their specific applications were discussed in depth. Question 2 was used to categorize the ML model that was tested. It alluded to the model's learning data type, the enormous amount of data it employs, and its widespread application in practice. The evaluation of ML models was the focus of Question 3. Specific examples of data, measurements, and results used in machine learning model evaluations were provided.

2.1. Search method

The authors took advantage of the search capabilities of Google and Scopus. ML, DL, open-pit slope stability prediction, dump slope failure prediction, and other relevant terms were used for this review. Machine learning and deep learning were used as search terms to identify papers that employ ML and DL strategies. The remaining keywords established the scope of the study. Figure 1 shows a peak in publications in 2022 and a trough in 2017.

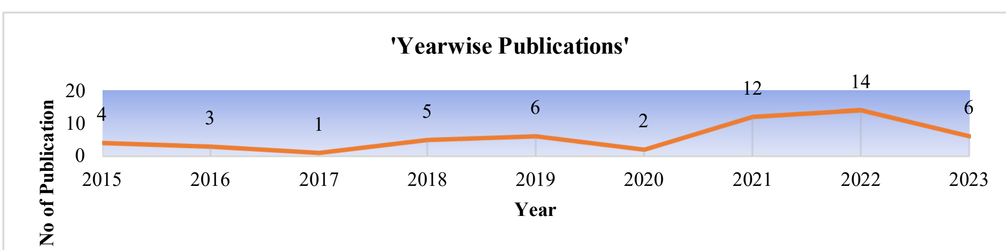


Figure 1. No of publications per year.

2.2. Flow chart of selection of papers

A flowchart for selecting appropriate publications to examine the topic of ML model applications in slope stability research is presented in Figure 2. Using ML algorithms and models to search for terms like "slope stability analysis" is the initial stage. Thereafter, the necessary articles were located, verifying that the complete article can be downloaded is the following step. The paper was downloaded if the article could be downloaded.

2.3. Research Question 1: Machine learning trends in slope stability analysis

2.3.1. Publication year

In the beginning, annual publications were considered to check the trends of machine learning applications in slope stability analysis. Figure 1 shows that the total number of publications has grown steadily. There were 12 and 14, respectively, published in 2021 and 2022.

2.3.2. Publication sources

Table 1 lists the various journals and the total number of articles published. Environmental Earth Sciences, Applied Sciences (Switzerland), and Natural Hazards published the most articles, as shown in Table 1.

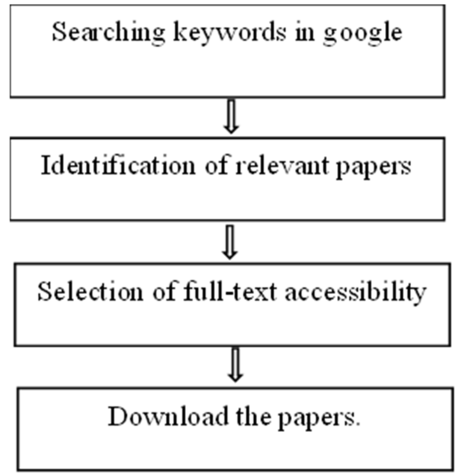


Figure 2. Flow chart to select relevant articles.

Table 1. The various journals/conferences and the total number of articles published.

Name of Journal/Conferences	No of Publications
3rd IEEE 2022 International Conference on Computing, Communication, and Intelligent Systems, ICCCIS 2022	1
Advances in Civil Engineering	1
Applied Mathematical Modelling	2
Applied Sciences (Switzerland)	3
Archives of Mining Sciences	1
Catena	1
Computer Software and Media Applications	1
Computers and Geotechnics	1
Computers and Industrial Engineering	1
Conference: AfriRock 2017 Rock Mechanics for Africa	1
E3S Web of Conferences	1
Energies	1
Engineering with Computers	2
Environmental Earth Sciences	4
Frontiers in Earth Science	1
Frontiers of Structural and Civil Engineering	1
Geomechanics and Geophysics for Geo-Energy and Geo-Resources	1
Geoscience Frontiers	1
GongchengKexueXuebao/Chinese Journal of Engineering	1
IEEE Access	1
International Journal for Numerical and Analytical Methods in Geomechanics	1
International Journal of Engineering and Computer Science	1
International Journal of Geophysics	1
International Journal of Optimization in Civil Engineering	1
ISPRS International Journal of Geo-Information	2
Journal of Rock Mechanics and Geotechnical Engineering	2
Journal of Scientific & Industrial Research	1
KSCE Journal of Civil Engineering	1
Land	1
Landslides	2
Natural Hazards	3
Proceedings - 2022 4th International Conference on Advances in Computing, Communication Control and Networking, ICAC3N 2022	1
Process Safety and Environmental Protection	1
Scientific Reports	1
Sensors	1
Soils and Foundations	1
Stochastic Environmental Research and Risk Assessment	1
Sustainability	1
Transportation Geotechnics	1
Water (Switzerland)	1

2.3.3. Machine learning methods

Figure 3 shows that the data-driven approach was the most popular method employed for slope stability analysis, with the hybrid approach being adopted by 38% of researchers, as given in Table 2.

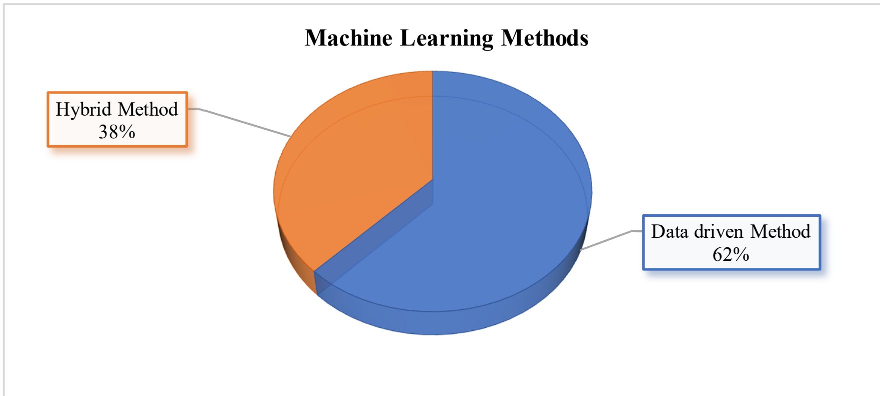


Figure 3. Machine learning methods.

Table 2. No of publications per ML approaches.

Machine learning methods	No of Publications
Data-driven method	[8], [19], [11], [1], [20], [10], [21], [22], [23], [16], [24], [17], [18], [25], [26], [27], [28], [6], [30], [29], [31], [32], [33], [34], [35], [13], [5], [12], [36], [37], [38], [39], [40], [41]
Hybrid method	[42], [15], [43], [44], [45], [46], [47], [48], [49], [2], [3], [4], [13], [9], [14], [50], [51], [52], [53], [54]

2.3.4. Input parameters/features for slope stability analysis

Machine learning systems for predicting slope stability rely heavily on input features. Figure 4 shows that the six input parameters of cohesion, bench height, unit weight, slope angle, internal friction angle, and pore water pressure were used by most researchers when assessing slope stability.

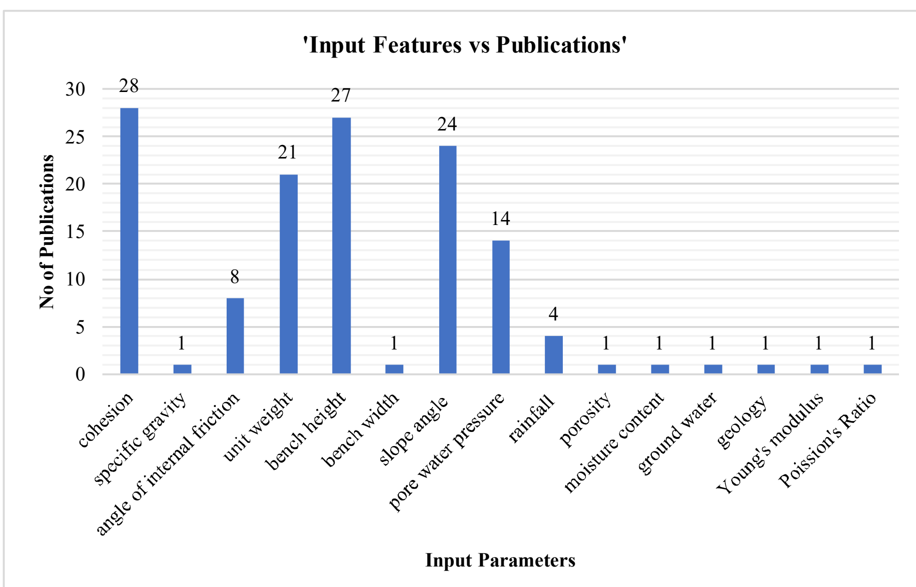


Figure 4. Input features vs publications.

2.4. Research Question 2: ML models
2.4.1. Dataset

ML studies have leveraged a wide variety of datasets. All of the data came from publicly available resources. This led to the data being divided into four groups: information that can be gained from open pit slope, dump slope, landslide, and past research. **Table 3** shows that most studies used historical research and landslide case articles as data sources for slope stability predictions.

Table 3. Dataset used in research articles.

Types of slopes	No of Publications	Reference
Pit slope	3	[42], [15], [43]
Dump slope	5	[44], [45], [11], [46], [47]
Landslide	24	[48], [19], [2], [3], [4], [9], [13], [14], [5], [29], [12], [15], [36], [37], [38], [39], [40], [41], [49], [50], [51], [52], [53], [54]
Past Research	21	[8], [1], [20], [10], [21], [22], [23], [16], [24], [17], [18], [25], [26], [27], [28], [6], [30], [31], [32], [33], [4], [46]

2.4.2. ML models

One binary classification model that uses a hyperplane to divide samples is the support vector machine (SVM) model. The fundamental principle of segmentation is to simultaneously maximize the interval to its maximum size and convert it into a convex quadratic programming problem. SVM is widely used for slope stability prediction since it outperforms other algorithms in scenarios with a small training dataset [8].

The RF algorithm is the improved version of DT. The way it works is by making several decision trees. It has been selected because of its reliability and correctness over many datasets [8].

DT is ML's foundational model for classification. Using basic decision-making rules learned from data attributes, it forecasts the value of target variables [8].

GBM is one of the most prevalent approaches to integrated learning. It has many decision-making features and can generate multiple trees [8].

The KNN algorithm is straightforward, making it easy to learn and use. Because the approach is robust against outliers, the prediction impact is practical and useful [8].

Based on the selected paper, the ML model was filed in the appropriate section. The authors reviewed the literature and found that RF and SVM were the most popular research methods, as shown in Figure 5.

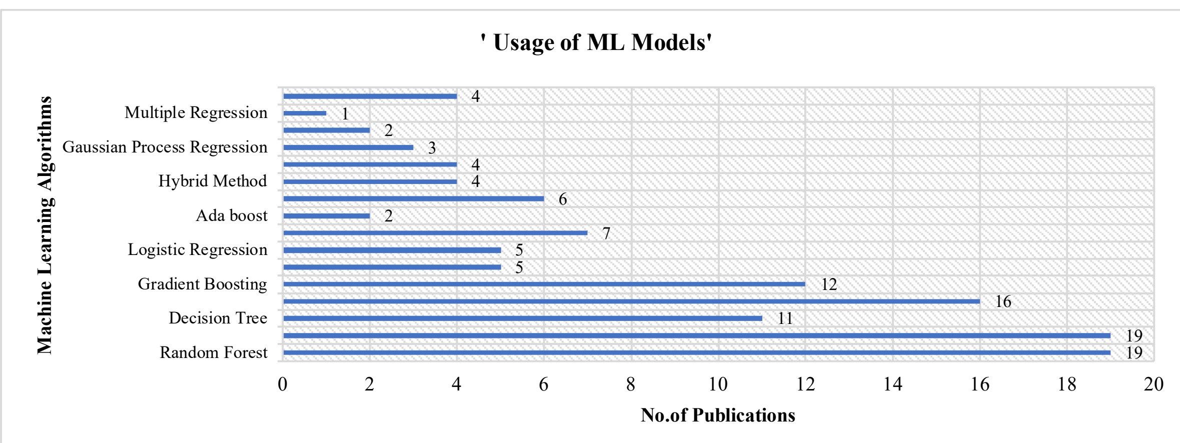


Figure 5. Usage of ML models.

2.5. Research Question 3:ML model evaluation
2.5.1. Model evaluation data

Data was necessary to measure how well ML models functioned. Data such as training data for realizing ML, validation data, and test data were provided to evaluate the correctness of the model once it had been trained. The best machine learning model can be chosen using validation data for model selection and verification. The performance of the chosen ML model is evaluated using test data [55]. Finally, evaluation metrics in Figure 6 were used to quantify the model's efficacy.

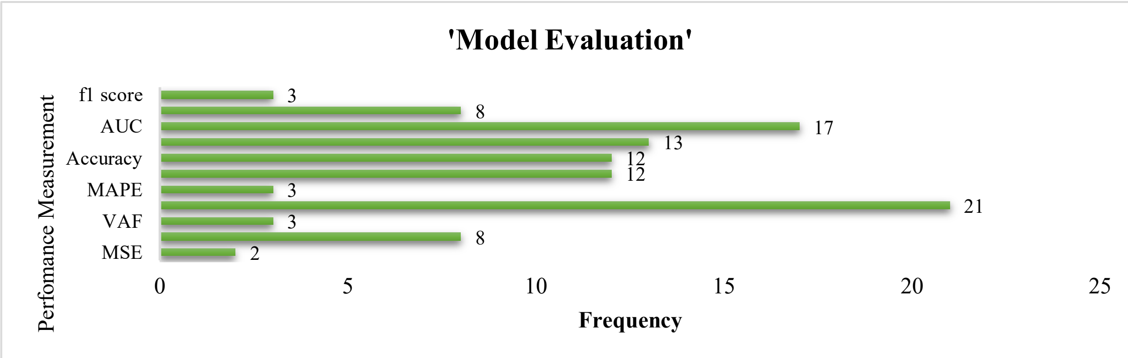
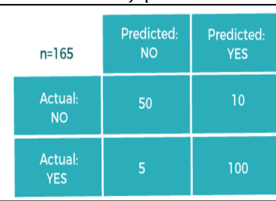
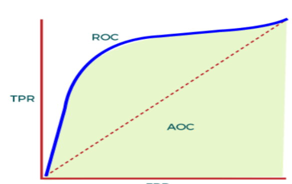


Figure 6. Different model evaluations.

2.5.2. Model evaluation metrics

The constructed ML model and several statistical methods were compared and constructed using evaluation metrics. The goals of the ML model were to determine the metrics used for assessment. However, several studies have utilized the same measures for evaluating ML models without considering their intended use. Evaluation metrics, as described in Table 4 & 5, such as the confusion matrix, f1-score, area under the curve (AUC), root mean square error (RMSE), mean absolute error (MAE), correlation coefficient, *Variability accounted for* (VAF), receiver operating characteristic (ROC), mean absolute percentage error (MAPE), accuracy, and mean square error (MSE) were used to evaluate the models. Figure 6 shows that RMSE and AUC were the most common metrics for assessing machine learning models. In addition to the above-mentioned measures, MAE, Accuracy, and ROC were also widely employed.

Table 4. Performance metrics for classification models.

Evaluation metrics	Description	Formula	Usages
Accuracy	It is the ratio of no of corrected predictions to the total number of predictions	$\frac{No\ of\ corrected\ predictions}{total\ no\ of\ predictions}$	Target variables are more balanced.
Confusion matrix	It is the result of a binary classifier's predictions presented in a tabular format, which illustrates how well the model performed on a dataset with known true values.		The predicted values are in the matrix's columns, whereas the actual values are in the rows. In this case, yes and no are the two alternative classes provided by actual and prediction.
Precision	The accuracy of the prediction is proportional to its precision.	$\frac{TP}{(TP+FP)}$ $TP = True\ positive$ $FP = False\ positive$	Accuracy has its limitations, but the precision metric helps get around them.
Recall or sensitivity	Its objective is to determine the percentage of incorrectly recognized actual positives.	$\frac{TP}{TP+FN}$ $TP = True\ positive$ $FN = False\ negative$	The accuracy of a classifier about false negatives is determined by its recall.
F-scores	It is an indicator for measuring the accuracy of a binary classification model's predictions for the positive class.	$2 * \frac{Precision * Recall}{Precision + Recall}$	Because F-scores consider both recall and precision, they are most valuable when evaluating something when both are relevant but where one is marginally more weighted.
ROC (Receiver Operating Characteristic) curve	The ROC plots the accuracy of a classification model against a range of threshold values.		To visualize the performance of classification models.

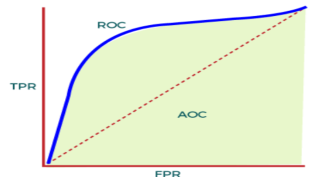
Area Under the ROC curve (AUC)	AUC calculates the two-dimensional area under the entire ROC curve		AUC should be utilized to evaluate the ranking of the predictions.

Table 5. Performance metrics for regression models.

Evaluation metrics	Description	Formula	Usages
Mean absolute error (MAE)	Mean Absolute Error (MAE) compares actual values to predicted values, with "absolute" denoting a positive value.	$\frac{\sum \lvert Y - Y' \rvert}{N}$ Here, Y = Actual value, Y' = Predicted outcome, and N = Total number of data	MAE considerably better handles outliers.
Mean squared error (MSE)	This metric calculates the mean squared deviation of the model's predictions from the actual values.	$\frac{\sum (Y - Y')^2}{N}$ Here, Y = Actual value, Y' = Predicted outcome, and N = Total number of data	Since it is differentiable, MSE is better optimized than other regression metrics, making it a popular choice.
R squared	Another popular metric for evaluating regression models is the R-squared error, another name for the coefficient of determination.	$1 - \frac{MSE(Model)}{MSE(Baseline}$	R-squared metric can be used to compare it to a constant baseline. To find out how well a model worked.
Adjusted R squared	It is an improved version of R squared.	$1 - \left[\left(\frac{n-1}{n-k-1}\right) \times (1 - R^2)\right]$ Here, n = Number of observations k = Number of independent variables	It accounts for variables that did not show statistical significance in the original regression.
Root mean squared error (RMSE)	It quantifies the disparities between predicted and actual values by squaring the errors, determining the mean, and obtaining the square root.	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^{\wedge})^2}$ Here, $y_i^{\wedge} = Predicted\ value$ $y_i = Actual\ value$	A smaller root-mean-squared error (RMSE) indicates better predicted accuracy, which gives a clear picture of the model's performance.
Mean absolute percentage error (MAPE)	Divide the absolute difference between the actual and predicted numbers by the actual value to get the mean absolute percentage error (MAPE).	$\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert y_i - y_i^{\wedge}\rvert}{y_i} * 100$ Here, $y_i^{\wedge} = Predicted\ value$ $y_i = Actual\ value$	Lower MAPE values indicate better model performance.

Pie charts were created to summarise the metrics findings of each ML model using four assessment markers utilized across multiple research (Figures 7–10).

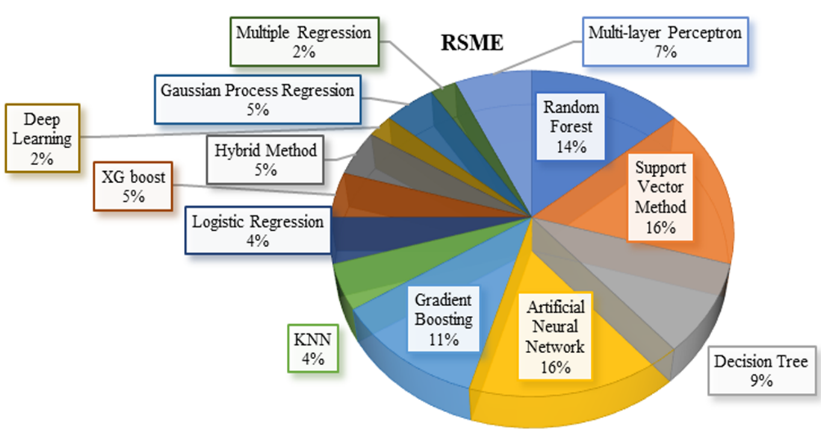


Figure 7. Root mean square error.

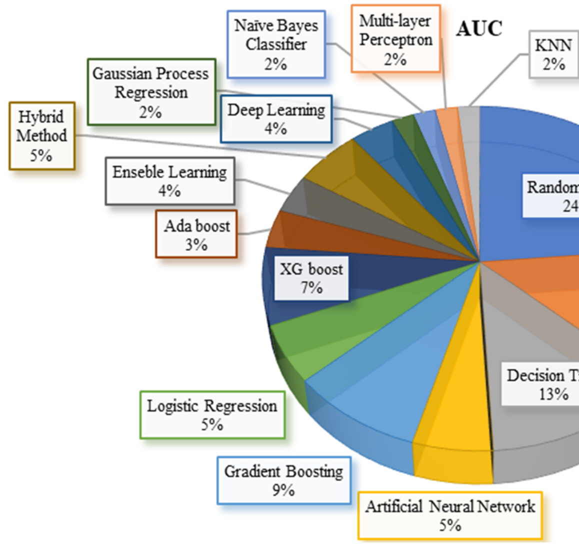


Figure 8. Area under curve.

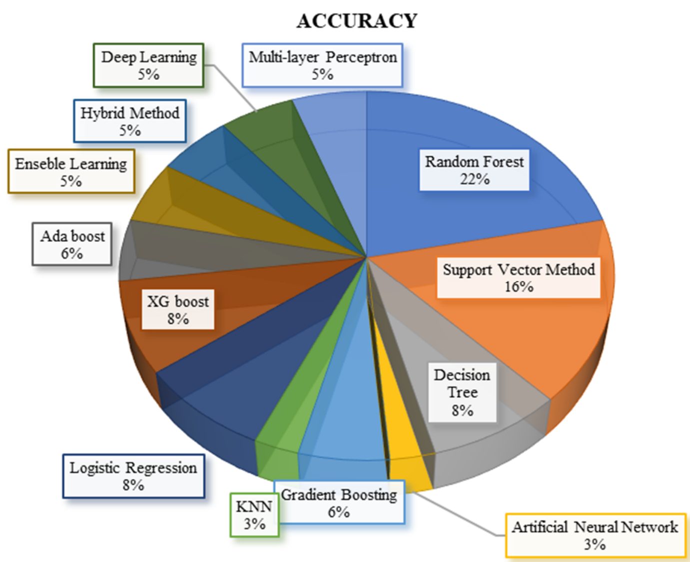


Figure 9. Accuracy.

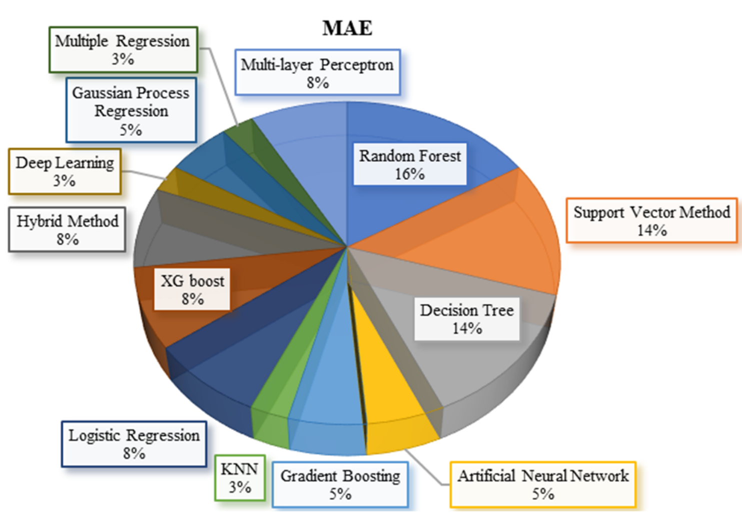


Figure 10. Mean absolute error.

3. Discussion

The following points were noted from the data presented in the Table 6 above:

While some researchers did use hybrid methods, the vast majority relied on data-driven approaches. Most studies examining the use of ML techniques for slope stability analysis have focused on landslide scenarios. Only a few of the stability of dump slopes and pit slopes have been considered in this study.

ML methods commonly employed to analyse slope stability include SVM, RF, and DT. A few researchers used ML methods such as DL, ensemble learning, LSTM.

It became clear that the input variables were considered limited for the studies. There needs to be a wide variety of both internal and external factors considered [56, 57].

Table 6. Comparative analysis of different ML models.

Reference	Field of application	Approach	Models	Input parameters	Findings
[8]	Landslide	Previous studied data	SVM, RF, KNN, DT, and GBM	γ, C, α, H, β, ϑ	It was revealed that random forest with KS cut-off was the optimal model and all other machine learning performed well with AUC score in between 0.824 to 0.964
[42]	Pit slope	Field study data	RF, LR, SVM, and KNN **Regression models**: DT, RF, and XGB	C, G, β, t, α, SC, WR, BC, and CBC	It was found that random forest outperformed the competition, but nearly every classification method got the failed case's misclassification right. Among all regression models, the decision tree regressor was the best regressor.
[44]	Dump slope	Field study data	SVM, RF, KNN, GRBT	H, β, and RI	It was concluded that in comparison to all the model's output GRBT was the superior model with high accuracy FOS (1.283) for the dump bench slope whereas numerical simulation analysis calculated FOS (1.289)
[19]	Landslide	Previous studied data	ANN	β, H, W, J1, J2	It was found an android app was developed using ANN which is very much capable to predict factor of safety of rock slope.
[1]	Landslide	Previous studied data	AutoML	γ, C, α, H, β, ϑ	AutoML outperformed with AUC (.970) and ACC (0.904).
[4]	Landslide	Previous studied data	(GPR), SVR, DT, LSTM, DNN, and KNN	γ, C, α, H, β, ϑ	It was revealed that the best model for predicting slope stability was the GPR model, which had the following metrics: R2=0.8139, RMSE =0.160893, and MAPE = 7.209772%.
[45]	Dump slope	Field study data	ANN and MRA	Crh, Sh, and Sa	It was found that in comparison to the MRA model, the ANN model's prediction accuracy is much higher, with a coefficient of determination value of 0.9996.
[11]	Dump slope	Previous studied data	SVR, ANN, RF, GBM and XGB	Hs, Hcd, BW, A, B, Hcr, α, and C	It was found that extreme gradient boost is well and truly above the support vector regressor regarding predictive performance. The effectiveness of different machine learning models in predicting the safety factor was also determined to be higher for the artificial dump slope compared to the residual soil slope that occurs naturally.
[3]	Landslide	Field study data	RF, XGB, SVM, and LR	E, H, β, I, DD, and LV, ST, PM, PS, and HA	The results demonstrate that XGB and RF outperform SVM and LR in terms of accuracy for both training and testing data, indicating that XGB and RF are the best ensemble learning models for predicting slope stability.
[13]	Landslide	Previous studied data	SVM, DT, KNN, ADA, RF, ANN, GCAB, and GBDT	H, β, and BD, C, α, and ϑ	It was concluded that for predicting FOS, the ANN and RF models performed better. They outperformed competing machine learning models with scores above 0.84 across both assessment techniques.
[9]	Landslide	Field study data	MLP, SVM, KNN, DT, RF	H, β, Dd, C, and α	It was found that the most effective model was the MLP, which achieved a 0.938 precision and a 0.90 accuracy rating.
[20]	Landslide	Previous studied data	RF and XGB	γ, H, α, C, and ϑ	It was found that the most effective evaluation model is XGB, which manages to reach 92% average accuracy, 91% precision, 96% recall, and an AUC of 0.95.
[14]	Landslide	Field study data	DL	γ, C, α	The results demonstrated that the suggested CNNs outperformed JCM by a factor of 18 when evaluating 200 examples, and this is before accounting for the time required to manually construct the LEMs.
[5]	Landslide	Previous studied data	SVR, BR, LR, ENR, KNN, ABR, GBR, Bagging, ETR, DT, and RF	γ, C, α, H, β, ϑ	It was found that one disadvantage to using ML as a regression method is that it is not completely automatic, so you can't just throw it out there and expect it to work. Repeated cross validation (CV) is required for slope data sets. The top three regression methods among eleven different ML algorithms are GBR, SVM, and Bagging.
[12]	Landslide	Previous studied data	SVM, Backpropagation, RF, and BN	UD, RI, ES	It was concluded that predicting slope failures was most effectively done by random forest (Accuracy=88%, AUC=0.915).

Table 7. Comparative analysis of different ML evaluation metrics.

Reference	Analysis	Field of application	Evaluation metrics
[8]	Classification	Landslide	ROC, AUC, confusion matrix
[42]	Classification and regression	Pit slope	Accuracy, confusion matrix, f1 score, RSME, MAE, MSE
[44]	Regression	Dump slope	RSME, MAPE
[19]	Regression	Landslide	RSME, R squared
[1]	Classification	Landslide	Accuracy, AUC, ROC, confusion matrix
[4]	Regression	Landslide	RSME, MAPE, MAE, R squared
[45]	Regression	Dump slope	VAF, RSME, R squared
[11]	Regression	Dump slope	VAF, RSME
[3]	Classification	Landslide	Confusion Matrix, Accuracy
[13]	Regression	Landslide	RSME, MAE, MSE
[9]	Classification and regression	Landslide	Precision, Recall, F1 score Accuracy, RSME, MSE and MAE
[20]	Classification	Landslide	Accuracy
[14]	Classification	Landslide	Accuracy
[5]	Regression	Landslide	R squared, MSE, MAE
[12]	Classification	Landslide	Accuracy, AUC

The following points were noted from the data presented in Table 7 above:

Regarding regression analysis, most researchers utilized RSME and MSE, while confusion matrices and accuracy were used for classification. When designing classification and regression models, it is essential to consider a broad range of evaluation metrics.

4. Application of ML models (case studies)

The following studies have compared the outcomes of numerical models with ML models for predicting factor of safety of the slope.

When calculating the safety factor of the slope, the ANN technique works effectively. Two outcomes were highly close to outcomes from numerical simulations. The discrepancy in the results is proportional to the size of the historical data-set. The current training set needs to be revised for the verification scenario since it does not include the history data of the slope near the geometrical parameters, mainly because the slope height was significantly varied. Data from various sources can enhance the model's prediction accuracy [13].

Findings using predictive models, especially multilayer perceptron (MLP), were as close to the FS value as those from the LEM technique [9].

With an absolute error of only 0.006, the safety factors computed by the gradient boosting regression tree (GRBT) are comparable to the LEM technique. This finding has important implications for the early warning of landslide disasters in open-pit mining dumps since it provides evidence that the landslide risk prediction model of these dumps, as described above, can accurately assess the landslide risk in these dumps [44]. Regarding slope stability analysis, it's clear that the machine learning models produce solid results that align well with those generated by LEM approaches [42, 58].

5. Conclusions

Recent developments in ML research on slope failure have been analyzed, and systematic reviews of relevant literature have been done. Extensive use was made of RF and SVM in slope failure prediction. Root-mean-squared error, accuracy, mean absolute error, and area under curve were extensively used to measure the performance of the ML model using test data. ML models with data-driven approach can be utilized for both real-time monitoring and slope stability prediction.

Several recent studies have employed ML approaches for slope stability prediction indicating an increasing interest in ML-related research, and it was verified that ML techniques could be successfully applied to predict the factor of safety of slopes. In addition, there is constant investigation into landslide phenomena. The authors have relied on accessible, open-source information. Data generated using ML methods and made publicly available is a valuable resource for scientists. When choosing a machine learning model, it is important to keep the study goals in mind. Commonly utilised models include random forest, artificial neural networks (ANN), and support vector machines (SVM) due to their flexibility in configuration. Depending on the goal of the research, a suitable assessment method can be chosen to assess the ML model's efficacy. Select RMSE and MAE if error minimization is the goal; accuracy and AUC if performance evaluation is the focus.

In this study, the authors looked at how several machine learning models have been applied to the problem of predicting slope stability, and the results provide information on the machine learning methods, input parameters, and evaluation metrics that have been employed. Only 53 papers related to this subject were taken into consideration. Therefore, future research can take advantage of the larger database to gain deeper insights and greater clarity on advanced technology in predicting slope failure.

List of Abbreviations

SVM - Support Vector Machine
RF - Random Forest
KNN - K-nearest neighbours
DT - Decision Tree
GBM - Gradient Boosting Machine
LR - Logistic Regression
XGB - XG bosting
GRBT - Gradient Boosting Regression Tree
ANN - Artificial Neural Network
AutoML - Automated Machine Learning
GPR - Gaussian Process Regression
LSTM - Long-Short Term Memory
DNN - Deep Neural Network
MR - Multiple Regression
GCAB - Guided Clustering Algorithm (bagging)
GBDT - Gradient Boosting Decision Tree
MLP - Multilayer Perceptron
DL - Deep Learning
BR - Bayesian Ridge
ENR - Elastic Net Regression
ABR - Adaptive Boosting Regression
GBR - Gradient Boosting Regression
ETR - Extra Trees Regression
BN - Bayesian Network models
SVR - Support Vector Regression
$\gamma =$ Unit weight
C = Cohesion
α = Internal angle of friction
H = Slope height
B = Slope angle
ϑ = Pore water pressure
G = Specific gravity
t = Thickness of layers
SC = Saturation Condition
WR = Wind and Rain
BC = Blasting Conditions
CBC = Cloud Burst Conditions
RI = Rainfall Intensity
W = Width
J1 = Joint one
J2 = Joint two
Crh = Coal-rib height
Sh = Dragline dump slope height
Sa = Dragline dump slope angle (Sa)
Hs = Height of the bench at dragline sitting level
Hcd = Height of the bench between the coal-rib roof and dragline sitting level
BW = Berm width at dragline sitting level
A = Angle of the face of the bench at dragline sitting level
B = Slope angle of the bench between the coal-rib roof and the dragline sitting level
Hcr = Coal-rib height
E = Front edge and back edge elevations
I = Inclination angle
DD = Dip Direction
LV = Landslide volume with five categorical variables-lithological property
ST = Structure type
PM = Plane Morphology
PS = Profile Shape
HA = Influence degree of human activities
BD = Bulk Density
Dd = Dry Density
UD = Upslope/Down slope angle
ES = Erosion and Susceptibility
CNN = Convolutional Neural Network

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کاربرد تکنیک های یادگیری ماشین در تحلیل پایداری شیب: مروری جامع

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چکیده:

صنعت معدن نیاز به پذیرش فناوری‌های خود مختار عصر جدید و سیستم‌های هوشمند دارد تا با نوسازی فناوری همراه باشد، به نفع سرمایه‌گذاران و ذی‌نفعان، و مهم‌تر از همه، برای ملت و حفاظت از سلامت و ایمنی باشد. بخش اساسی مهندسی ژئوتکنیک انجام تجزیه و تحلیل پایداری شیب برای تعیین احتمال شکست شیب و نحوه جلوگیری از آن است. یک تکنیک قابل اعتماد، مقرون به صرفه و به طور کلی کاربردی برای ارزیابی پایداری شیب به فوریت مورد نیاز است. مطالعات تحقیقاتی متعددی انجام شده است که هر کدام از یک استراتژی منحصر به فرد استفاده می کنند. یک روش جایگزین که از تکنیک‌های یادگیری ماشین (ML) استفاده می‌کند، مطالعه رابطه بین شرایط پایداری و ویژگی‌های شیب با تجزیه و تحلیل داده‌های جمع‌آوری‌شده از پایش و آزمایش شیب است. این مقاله تلاشی از سوی نویسندگان برای بررسی جامع ادبیات استفاده از تکنیک‌های ML در تحلیل پایداری شیب است. مشخص شد که اکثر محققان به رویکردهای داده محور با متغیرهای ورودی محدود تکیه می‌کنند و همچنین تأیید شد که تکنیک‌های ML می‌توانند به طور مؤثر برای پیش‌بینی تحلیل شکست شیب مورد استفاده قرار گیرند. SVM و RF محبوب ترین انواع مدل های ML مورد استفاده بودند. RMSE و AUC به طور گسترده در ارزیابی عملکرد مدل‌های ML استفاده شدند.

کلمات کلیدی: پایداری شیب، ضریب ایمنی، مدل‌های یادگیری ماشین، ماشین بردار پشتیبان، جنگل تصادفی (RF).