

Slope Stability Assessment and Prediction Via Machine Learning Techniques for Improved Safety and Reliability: A Systematic Review

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Abstract: During the last few decades, there has been a significant advancement and widespread application of machine learning (ML) in slope stability analysis. ML is particularly useful when employed as an alternative model to increase efficiency. This study presents a systematic review of the application of ML classifiers in slope stability analysis, focusing on their role in improving safety and reliability. A total of 46 studies published within the past seven years, from 2018-2024, are reviewed to assess the efficacy of ML-based approaches in slope stability assessment and prediction. The review encompasses two main aspects: safety factor prediction and evaluation of ML algorithms in predicting the Factor of Safety (FOS) for slope stability. The key findings regarding the performance of ML methods are synthesized through a rigorous screening process utilizing the SCOPUS database and following predefined inclusion criteria outlined in the PRISMA model. Various ML techniques are examined for their efficacy in predicting FOS, a critical parameter in slope stability analysis. Performance evaluation of ML algorithms across multiple metrics reveals significant findings. Further, the review highlights the importance of ML in slope stability assessment and underscores its potential for enhancing predictive capabilities. Overall, the study provides insights into the advancements and challenges associated with integrating ML techniques in slope stability analysis, laying the groundwork for further studies and practical applications in engineering practices.

Keywords: Slope stability; slope stability prediction; machine learning (ML); factor of safety (FOS); Slope reliability; systematic review

1. Introduction

The stability of slopes is an important concern that must be thoroughly examined due to their significant effect on nearby engineering projects [1]. Furthermore, slope collapses result in significant psychological harm, such as the destruction of property and loss of human life, occurring globally on an annual basis [2]. According to the Iranian Landslide Working Party (2007), about 187 individuals in Iran lose their lives each year due to slope failure [3]. The various factors that affect the slope stability are illustrated in Figure 1 given below.

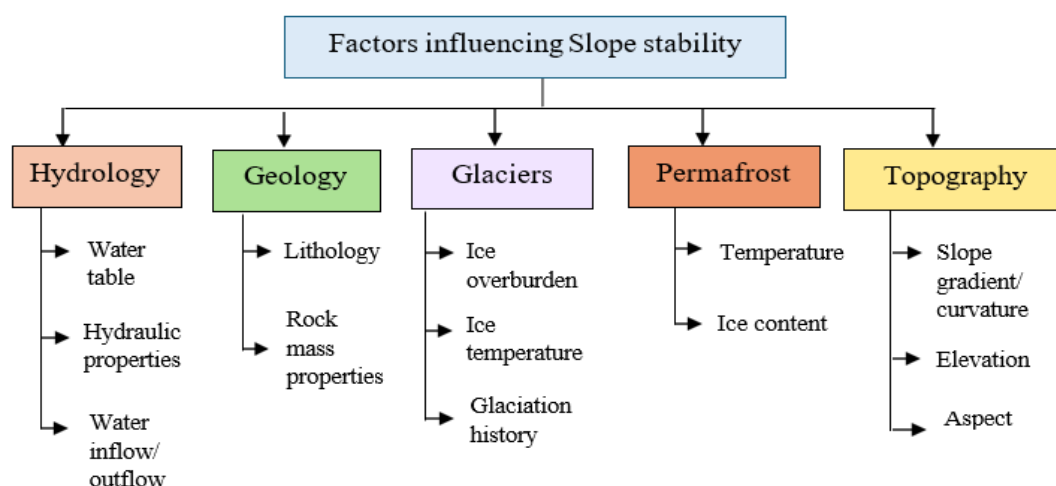


Figure 1. Factors influencing slope stability [4].

Landslides are spontaneous and severe natural calamities that may exert substantial harm on neighbouring structures, leading to financial and human losses [5-8]. Hence, the assessment of slope stability is an essential need for preventing and minimizing the impact of disasters [9]. Slope stability study focuses on the examination of earth materials, including soil, rock, and other substances [10]. Soil is an engineering material with very intricate mechanical, physical, and chemical characteristics, consisting of three different stages. The geographical diversity and anisotropy of soils, caused by geological activity and stress history, provide challenges in examining and forecasting their behaviour. The saturation degree, along with other inherent characteristics of the soil, greatly influences the probability of slope failure [11]-[12]. Currently, several studies have tried to develop efficient models to address slope stability issues [13-15]. Several limitations of conventional approaches, such as the need for laboratory resources and the significant degree of difficulty, restrict their practical use. Furthermore, their effectiveness is limited in assessing certain slope conditions such as slope angle, height, groundwater level, and soil qualities, making them inadequate as a complete solution.

Numerous quantitative solutions, finite element models (FEMs), and limit equilibrium techniques (LEMs) have been used to address the engineering challenge [16-19]. Partial slope stability is affected by two factors: the quantity of surcharges and its position from the slope's crest. Because of this, researchers have proposed an algorithm to determine the FOS of pure slopes or slopes subjected to a static load [20-23].

An effective method for evaluating slope stability has been the subject of numerous studies which led to the creation of design charts for a long time [24]. Still, there are some drawbacks to this method. A significant investment of time and resources is necessary to generate an effective design chart. In addition, it is not easy to determine the exact mechanical characteristics [25]-[26]. Therefore, Artificial intelligence (AI) approaches are getting more attention because of how fast they work and how accurate they are.

Furthermore, the number of hidden nodes used to build ANN may be freely adjusted [27]. For instance, several geotechnical research has shown the effectiveness of artificial neural networks (ANNs) [28-30] and support vector machines (SVMs) [31]-[32]. While there has been a lot of work using different soft computing methods to assess slope stability [33]-[34], no research has yet addressed a thorough comparison of the models offered by different studies. Hence, this study presents a Systematic review of Slope stability assessment and prediction for improved safety and reliability.

1.1. Slope Stability Prediction

Forecasting the stability of slopes is a major obstacle in the field of geological and geophysical engineering [35]. When representing soil, rock, or mixed mass, slope stability is essential because it shows how different faults cause detachable masses to move downward on a slope [36]. Slope failures are a common geological calamity that happens naturally and is a major threat to many countries [37]-[38]. Facilities, roads, trains, infrastructures, and foundations are all vulnerable to the distortion of the ground that results from slope failure [39-41]. The public and individual property is damaged to the extent of several hundred million dollars annually, and as a result, there are always substantial social and economic consequences [42]-[43]. Professionals and scientists had to assess the slope's stability and determine how to prevent or mitigate the harm that it was causing immediately. However, there are a lot of input parameters, and the technique is rather complicated. There is a great deal of unpredictability in the affecting elements, which include things like the moisture amount in the soil, the resistance to shear of geomaterials, and the geometric structure [44]. These precipitating variables are used to ascertain the sliding mass's behaviour and the potential for growth of the slip surface on slopes. Soil particle shear durability and strength may both decrease due to weathering and erosion, which can lead to slope sliding [45]-[46].

A significant number of slope stability studies employ the Factor of Safety (FOS) as a way to generalize and assess the entire strength and weakness of the slope [47-49]. Precisely assessing slope stability requires a very complex calculation that demands significant time and effort. Various analytical and numerical methods are used to determine the FOS of a certain slope [50]-[51].

1.2. Traditional Approaches in Slope Stability Analysis

Geotechnical engineering generally employs two primary techniques for examining the physical characteristics of geological substances: numerical/analytical approaches and empirical approaches. Slope stability in numerical models is quantified as a Factor of Safety (FOS), which is determined through deterministic methods like limit analysis [52], finite element limit method [53], finite element method based on displacement utilized with the strength reduction technique [54], or finite element evaluation with the gravity increasing technique [55]. An extensively utilized traditional technique is the LEM [56]. However, the process involves establishing an assumption about a pre-established key failure surface where failure is expected to occur and then calculating the resistance force by a mathematical equation. Alongside LEM, finite difference method (FDM) and FEM have also evolved as advanced numerical analysis (NA) approaches capable of effectively addressing complex slope stability problems with higher efficiency.

Due to the emergence of statistical approaches, various studies in geotechnics have started considering the use of random field theory to quantify the safety margin of slopes [57]. The simplicity, adaptability, and user-friendliness of the brute-force Monte Carlo simulation (MCS) approach have contributed to its rise in popularity within reliability assessment. In theory, the MCS could handle any issue, including sensitivity assessment, risk evaluations, and parameters inversions [58]. Despite this, brute-force MCS is computational and time-intensive when dealing with large sample sizes [59-62]. After that, RSM (the response surface technique) was suggested and subsequently utilized extensively [63]-[64]. Because this analytical function type substitutes the precise limit state, the number of

computations needed to evaluate the stability of structural systems may be drastically decreased. Despite this, numerical approaches are sometimes inadequate in explaining complicated real-world scenarios since they are oversimplified responses to realistic issues because empirical approaches may immediately provide the FOS or slope stability classification, which might be utilized as independent as well as dependent variables in reliability analysis.

Despite its numerous advantages, the method does have some disadvantages, such as the lengthy period required for numerical simulation [65]. These methods also need precise limits that can reproduce the real-world field scenario for improved accuracy, which isn't always easy to establish. There is a need for a new approach that can provide faster and more accurate findings because of the complexity and shortcomings of current approaches [66].

1.3. Evolution of machine learning in slope stability

In the last few years, researchers in the field of geotechnics started investigating ML approaches as a potential approach to examine slope stability. Several studies have shown promising results when employing ML-assisted stochastic analysis [67–71]. There has been research from a number of countries that has used ML to help in slope stability evaluation. Forecasting safety factors or classifying slope safety using data from field testing is a common subject of this research. Several slope classifications have been performed using data gathered from all across the world, [72]–[73]. In order to better estimate FOS, the stability study of earth slopes using predictive models benefited significantly from advanced technology, particularly artificial intelligence (AI). Forecasting and evaluating the FOS based on ML performance and specific accuracy are two goals of predictive models [74]. Machine learning algorithms use training data to comprehend the target data's present state, learn, and act on that acquired knowledge.

ML models have the potential to effectively forecast the desired result in geotechnical reliability evaluations by identifying complicated correlations among input and output data and constructing highly dimensional nonlinear equations [75]. When faced with uncertainty, ML-generated surrogate models perform well. They are able to consider data variation, which includes soil and slope parameter variations; model variation, which includes different initialization values; model frameworks hyperparameters evaluation; and validation variability, which includes distinct indicators for evaluation. Soil mechanical characteristics and slope boundary parameters are often inputs for slope stability issues, with the FOS or slope stability prediction as the output [76].

Machine learning makes use of a wide variety of algorithms, including both shallow and deep learning approaches. The goal of these methods is to obtain conclusions and predictions [77]. A learning paradigm, such as supervised, unsupervised, or reinforcement learning, might correlate to an algorithm's learning rate, which in turn directly affects the accuracy of the predictions [78]. It is possible to evaluate the efficacy and precision of any algorithm by analyzing its performance, regardless of the learning method used for predictions [79]. Some of the benefits of ML techniques over more conventional statistical or analytical approaches include their high accuracy, ability to process huge datasets, management of incomplete data, and the fact that they do not need any starting hypotheses about input and output [80–83]. Geotechnical engineers could employ ML approaches to avoid the drawbacks of conventional methods, such as heavy computing demands and the need to predict slope stability.

The motivation behind this study lies in the pressing need to enhance safety and reliability in geotechnical engineering, particularly concerning slope stability. Traditional methods for assessing slope stability may fall short in capturing complex interactions, prompting exploration into ML techniques for more accurate predictions. The study aims to provide a comprehensive and insightful analysis of slope stability assessment and prediction using ML techniques, contributing to improved safety and reliability in geotechnical engineering practices.

The document is organized in the following way: The opening section provides a short overview of the subject matter. The second section of the paper presents a review method that is used to perform the study along with the Prisma model which was designed to show the selection criteria of the papers systematically. Then, it proceeds with the thematic analysis of the literature reviews. The next section is a discussion; after this, the conclusion of the paper is offered, and in the last section, notations followed by a bibliography are presented.

2. Review Methodology

PRISMA statement is considered as the screening criteria to refine the research. The SCOPUS database has been used to get a comprehensive literature assessment on this phenomenon, encompassing records published from 2018 to 2024. This review includes all records categorized as articles, journals, and publications from the Scopus database. Table 1, given below, shows the keywords that are used in the Scopus database to find the papers related to the topic.

Table1. Searching Keywords

Databases	Keywordused
Scopus	(TITLE-ABS-KEY ("Slope stability" OR "Slope failure" OR "Slope assessment")AND TITLE-ABS-KEY("Machinelearning"OR"DeepLearning"OR"ArtificialIntelligence") ANDTITLE-ABS-KEY("factorofsafety"OR"safetyfactor"OR"slopereliability"))

Source: Authors own elaboration

For the literature analysis, all records, including articles, conference papers, etc., are marked countable and evaluated for assessment. The below-presented Table 2 exclusively examined records that met the specified inclusion and exclusion criteria.

2.1 Prisma Model

The reviews are guided by the PRISMA Statement “Preferred Reporting Items for Systematic Reviews and Meta-Analyses”. PRISMA demonstrates the ability to review and enables readers to understand its advantages and disadvantages as well as replicate review strategies.

Figure 2 illustrates the detailed systematic procedure for data extraction. This process encompasses retrieving research articles, performing source analysis, filtering out irrelevant materials according to predetermined criteria, and ultimately examining the content of the source research papers. A specific timeframe spanning seven years (2018-2024) has been allocated for conducting an exhaustive systematic literature review to identify relevant papers within the topic area. The studies included in the review are sourced from the Scopus database, assessed as of May 3, 2024. Following the application of automated tools to eliminate ineligible studies based on provided keywords related to slope stability assessment, a total of 148 studies were identified. This number is very significant as it shows that the most relevant keywords are used that lead to precise results.

Out of the 148 identified records, 26 records are excluded based on the Year, i.e., the studies previous than year 2018 are excluded, and only 122 are considered for screening. After screening, 1 paper is excluded based on document type, 6 papers are excluded based on publication stage, and 4 papers are excluded based on language. After exclusion, 111 reports are then assessed for eligibility. These papers are then exported in CSV format for further analysis. Out of the assessed reports, 65 are excluded due to insufficient data, irrelevant study, improper methodology and evaluation parameters after manually reading the papers. Finally, a total of (n=46) reports of new studies are included after the final filtering process, which are considered for analysis.

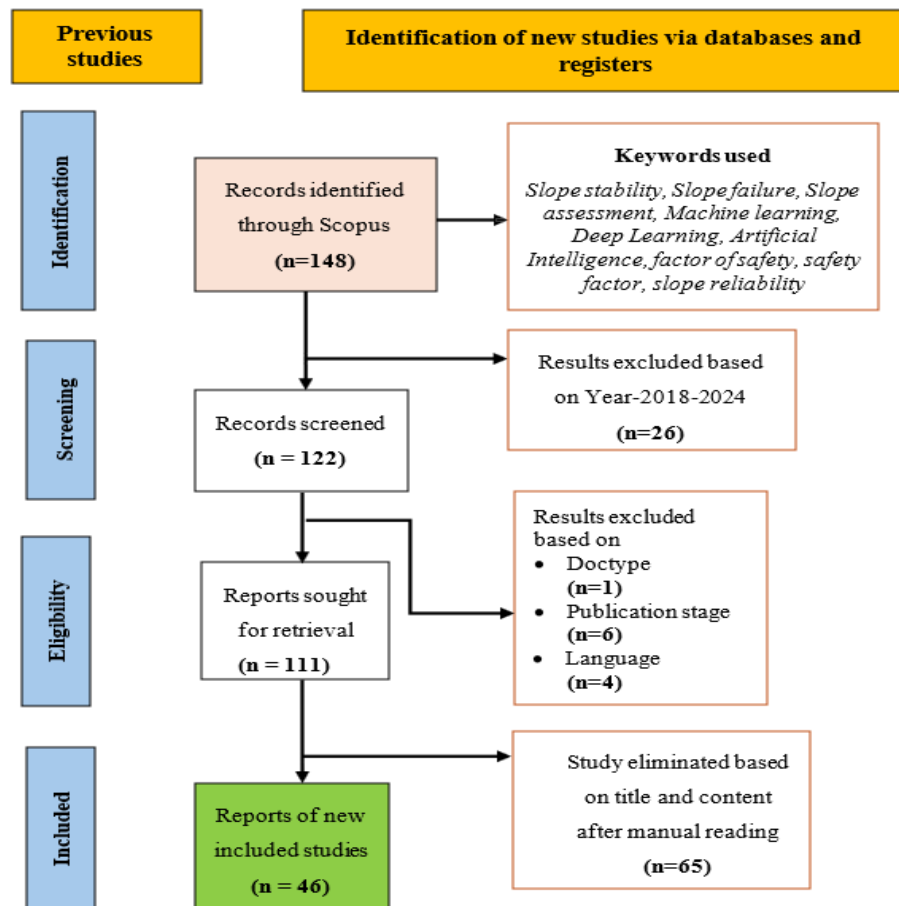


Figure 2. A PRISMA-based flowchart for systematic reviews of publications found in the database

Figure 3 demonstrates the top 5 areas that were most extensively studied based on specific criteria. The figure shows that Earth and Planetary Sciences have the most published articles, i.e., 58, followed by Engineering, which has 51 published articles. In computer science, there were 32 articles, followed by Environmental Science and Material Science, which have 22 and 13 published articles respectively.

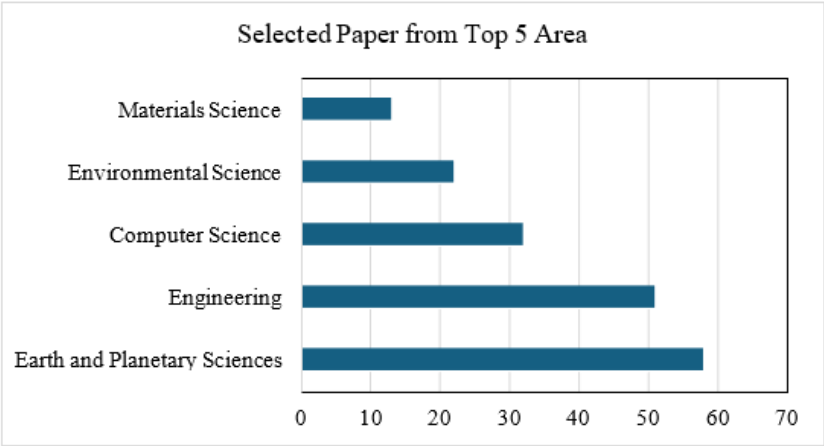


Figure 3. Selected papers from the top 5 Areas
Source: Authors own elaboration

The analysis of the literature on slope stability analysis research reveals several keywords, as shown in Figure 4. With 88 papers dedicated to slope stability, there is a substantial focus on determining the stability of various slopes. ML emerges significantly with 53 papers, showcasing its prevalent use in predicting slope stability. Additionally, the emphasis on the Factor of safety or safety factor is evident in 56 and 28 papers, underscoring the importance of its prediction for stability assessment of slope. The presence of 25 papers dedicated to stability analysis indicates efforts to develop methods that facilitate improved safety and reliability of slope. These findings collectively provide valuable insights into prevailing trends of ML in slope stability prediction.

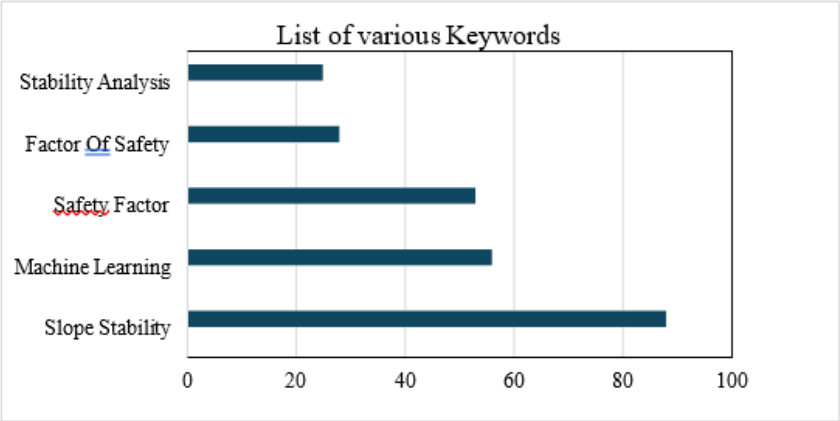


Figure 4. List of various Keywords
Source: Author own elaboration

Figure 5 offers valuable information regarding the years in which the papers were published. For this systematic literature review, the terms that were searched were selected specifically to explore slope stability assessment and prediction using ML.

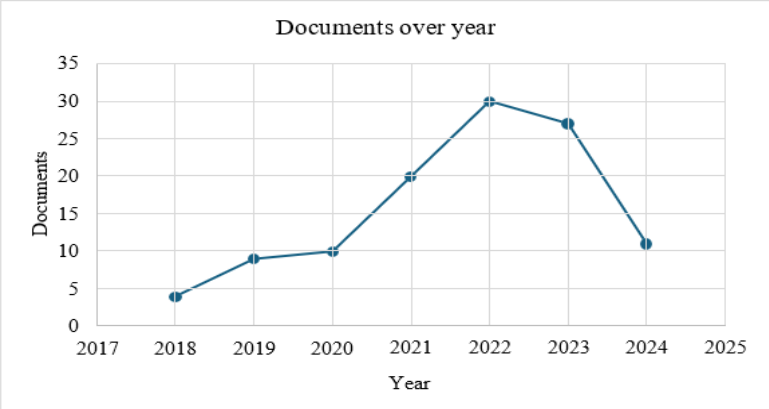


Figure 5. Trend in published papers
Source: Authors own elaboration

3. Literature analysis

This literature review focuses on slope stability assessment and prediction using ML techniques, aiming to enhance safety and reliability in various applications. It systematically analyses existing research papers within the specified timeframe of 2018-2024, sourced from the Scopus database. By employing a structured process of data extraction, source analysis, and filtering based on predefined criteria, the review identifies relevant studies for comprehensive analysis. The overarching goal is to provide insights into the effectiveness and applicability of ML methods in predicting slope stability, thereby contributing to advancements in engineering practices, hazard mitigation strategies, and infrastructure development.

3.1 Slope stability analysis through FOS prediction with ML

ML algorithms have emerged as a promising avenue for enhancing slope stability analysis and risk management strategies. Shui et al. (2023) and Khajehzadeh et al. (2023) introduced unique models for predicting slope safety factors, demonstrating the efficacy of Stacking- SSAOP and global-best artificial electric field-support vector regression (GBAEF-SVR) models, respectively. These models incorporate various input variables such as density, cohesion, friction angle, and slope characteristics to yield predicted FOS values, thereby refining slope stability assessments. Similarly, Wang et al. (2023) and Ma et al. (2022) proposed innovative approaches integrating ML algorithms like Improved Sparrow Search Algorithm with back propagation neural network (ISSA-BP) and Multi-Kernel Relevance Vector Machine Advanced First-Order Second Moment (MKRVM-AFOSM) and compared the outcomes with traditional methods to predict FOS, contributing valuable insights to slope stability analysis.

Furthermore, various studies demonstrate the potential of ML techniques in enhancing slope stability analysis across different contexts. Jiang et al. (2022) utilized the Gradient Boosting Regression Tree (GBRT) algorithm to predict FOS values and compared it with LEM in energy mining contexts, highlighting the role of AI in disaster prevention strategies. Conversely, Zheng et al. (2021) integrated ML techniques like Least Squares SVM (LSSVM) with traditional geotechnical methods to evaluate slope reliability, offering valuable contributions to slope stability analysis in heterogeneous soil conditions. Additionally, Deng et al. (2021) and Falae et al. (2021) employed LEM and FEM, respectively to obtain FOS and compared it with Multivariate Adaptive Regression Splines (MARS) to assess probabilistic slope stability, emphasizing the significance of integrating advanced modelling techniques for landslide risk assessment. Collectively, these studies underscore the potential of combining traditional geotechnical practices with ML methodologies to advance slope stability analysis and improve risk management strategies in geotechnical engineering.

Key findings from the survey of material available in the open literature

Table 3 shows the comparative analysis of several studies applied to FOS prediction. Figure 6 illustrates the findings presented by the authors for FOS prediction.

Table 3. Literature review

Author	Method to obtain FOS	ML Method/ technique	Input Variables	Predicted FOS
Shui et al., (2023) [84]	FEM	Stacking-SSAOP model	$\rho, c, \phi, \beta, H, r_u$	0.03917
Khajehzadeh et al., (2023) [85]	LEM	GBAEF-SVR	ϕ, c, γ, r_u	1.316
Wang et al., (2023) [86]	Empirical method	ISSA-BP	$\phi, H, c, \beta, r_u, w_s$	1.231
Ma et al., (2022) [87]	LEM (Bishop method)	MKRVM-AFOSM	c, ϕ, γ	1.044
Jiang et al., (2022) [88]	LEM	GBRT	H, β, R_d, R_i	1.283

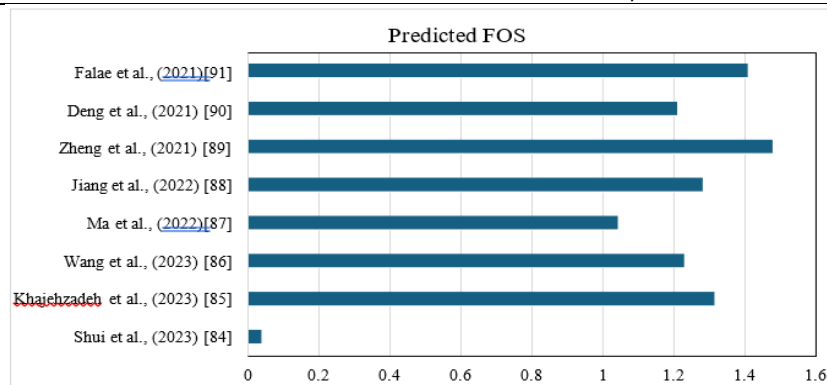


Figure 6. Findings presented by the Authors

3.2 Evaluation of ML Approach for FOS Prediction on various Performance metrics

In this section of the literature review, we delve into the comprehensive evaluation of ML approaches concerning the prediction of FOS for slope stability. Various studies have examined these methodologies across a spectrum of performance metrics, crucially focusing on accuracy, R-squared error (R²), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). This section synthesizes findings from diverse studies, providing valuable insights into the effectiveness and applicability of ML techniques for slope stability analysis, thus contributing to the advancement of geotechnical engineering practices.

(i) Based on Accuracy

In recent years, the application of ML approaches in predicting FOS for slope stability analysis has garnered significant attention in geotechnical engineering research. Various studies have explored the effectiveness of ML algorithms such as Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), Multilayer Perceptron (MLP), SVMs, ANNs, Decision Trees (DT), Random Forests (RF), and k-nearest Neighbours (KNN) in assessing slope stability.

Wei et al. (2024) introduced a novel integration of CNN with Infinite Slope Stability Analysis (ISSA) for regional landslide susceptibility mapping, while Li et al. (2023) developed a DNN-based surrogate model. Nanehkaran et al. (2023) compared ML classifiers like MLP, DT, SVM, and RF for predicting slope safety factors, while Liu et al. (2023) proposed the optimum-path forest-based KNN (OPF-KNN) method. Ahangari Nanehkaran et al. (2022) utilized MLP for safety factor estimation, and Deris et al. (2021) compared SVM and DT for slope failure prediction and proposed another study to evaluate the accuracy of Grey relational analysis-artificial neural network (GRANN) in FOS prediction.

Additionally, studies by Hong et al. (2021), Azmoon et al. (2021), and Chebrolu et al. (2020) explored the efficacy of KNN, CNN, and Multi-gene Genetic Programming (MGGP), respectively, in slope stability analysis. These research efforts collectively demonstrate the increasing reliance on ML and deep learning techniques for enhancing slope stability analysis, offering valuable insights and innovative approaches for geotechnical engineering practices.

Key findings from the survey of material available in the open literature

Table 4 shows the comparative analysis of several ML algorithms applied for FOS prediction based on accuracy.

Table 4. Literature review

Author	ML Method/ technique	Input Variables	Accuracy (%)
Weietal.,(2024)[92]	CNN+ ISSA	γ, c, ϕ	80.3
Lietal.,(2023)[93]	DNN	H, β, c, ϕ	92.22
Nanehkaranetal.,(2023)[84]	MLP	H, GWL, N_L, D_t, D_s	90.1
Liu et al.,(2023)[94]	OPF-KNN	$\gamma, c, \phi, \text{the } \beta, H, r_u$	90.1
AhangariNanehkaranetal., (2022) [95]	MLP	H, β, ρ, c, ϕ	93.8
	RBF-(radialbasis function) SVM		
Deriset al.,(2021)[96]		$\gamma, c, \phi, \beta, H, r_u$	96.67
Hong et al.,(2021) [97]	KNN	c, ϕ, E, μ	95.0
Azmoon et al.,(2021) [98]	Deep learning(CNN)	c, ϕ, γ	99.71
Deriset al.,(2021)[99]	GRANN	$\gamma, \phi, c, r_u, H, \beta$	99.99
Chebrolu et al.,(2020)[100]	MGGP	$\gamma, c, \phi, \beta, H, r_u$	85.71

Figure 7 illustrates the findings presented by the authors for evaluating the performance of ML techniques in FOS prediction based on accuracy.

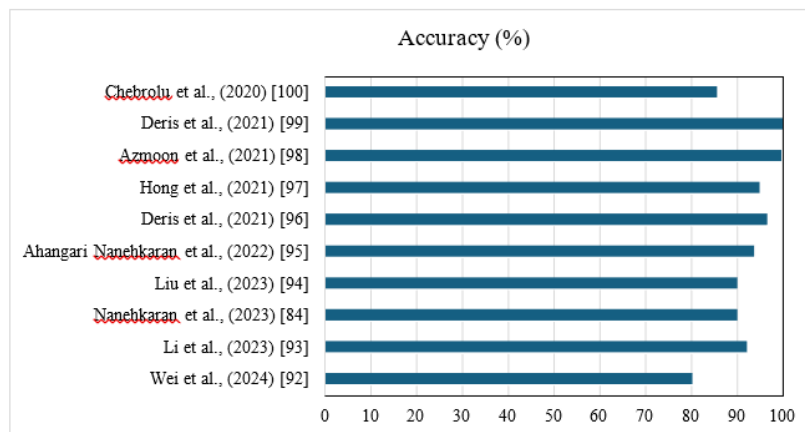


Figure 7. Findings presented by the Authors

(ii) Based on R^2 error (R^2)

A series of recent studies underscore the significance of slope stability in various engineering contexts. Ragam et al. (2024) highlighted the transition from traditional prediction methods to ML solutions in mining operations, particularly evident in their study at OstapalChromicte Mine, India, where the XGBOOST-RF ensemble model emerged as a highly accurate tool for estimating FOS. In a complementary vein, Ahmad et al. (2024) proposed ensemble ML methods for predicting FOS in railway embankments, showcasing the proficiency of the voting ensemble (VO-ENSM) model.

Additionally, Pandey et al. (2022) emphasized the criticality of predictive modelling in averting slope failures, especially in hilly regions, with their deep learning approach demonstrating superiority in accurately predicting safety factors for excavated slopes. Meanwhile, Hanandeh et al. (2022) contributed insights into slope stability analysis by developing models for stability status classification and FOS estimation, exhibiting superior performance in both aspects. Furthermore, Foong et al. (2022) suggested combining metaheuristic optimizers with ML models, highlighting the equilibrium optimization (EO) MLP as an effective tool for enhancing accuracy in slope stability evaluation.

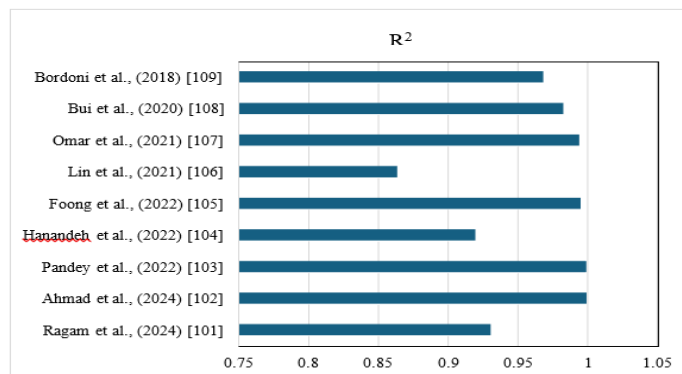
Parallely, Lin et al. (2021) presented an ML model tailored for slope stability assessment, identifying SVM, gradient boosting regression (GBR), and bagging as top-performing regression methods. Meanwhile, Omar et al. (2021) leveraged AI methods to evaluate slope stability on soft ground, achieving promising results with factors of safety predicted using ANN and Adaptive Neural Fuzzy-Logic Inference Systems (ANFIS). Moreover, Bui et al. (2020) focused on developing a highly accurate AI model for slope failure prediction in open-pit mines, introducing the M5Rules–GA hybrid technique, which outperformed other investigated models. Lastly, Bordoni et al. (2018) demonstrated the potential of SVM models in accurately predicting soil water content, which is crucial for assessing shallow landslide triggering, thus showcasing SVM's applicability in slope stability analysis.

Key findings from the survey of material available in the open literature

Table 5 shows the comparative analysis of several ML algorithms applied for FOS prediction based on R^2 error. Figure 8 illustrates the findings presented by the authors for FOS prediction.

Table 5. Literature review

Author	ML Method/technique	Input Variables	R^2
Ragam et al., (2024) [101]	XGBOOST-RF ensemble model	$\gamma, \phi, c, D_m, \beta$	0.931
Ahmad et al., (2024) [102]	VO-ENSM	c, ϕ, γ	0.9997
Pandey et al., (2022) [103]	ANN-adam	c, ϕ, H, β	0.9996
Hanandeh et al., (2022) [104]	Genetic algorithm (GA)	$c, \gamma, \beta, r_u, H, \phi$	0.92
Foong et al., (2022) [105]	EO-MLP	$C_u, \beta, w, b/B$	0.9954
Lin et al., (2021) [106]	SVR	c, β, H, γ	0.8640
Omar et al., (2021) [107]	ANN	$H, \gamma, S_m, \beta, c, \phi$	0.99454
Bui et al., (2020) [108]	M5Rules–GA model	$H, \gamma, c, \phi, \beta$	0.983
Bordoni et al., (2018) [109]	SVM	γ, ϕ, c	0.9686

**Figure 8. Findings presented by the Authors**

(iii) Based on Root Mean Square Error (RMSE)

Several recent studies have made significant strides in advancing the field of slope stability prediction through the application of diverse methodologies and techniques. Chen et al. (2023) proposed a novel model integrating deep learning and digital twinning methods to simplify safety factor calculations based on geological and physical data. Soranzo et al. (2023) introduced a CNN model tailored for predicting the FOS in random layered slopes utilizing the strength reduction method. Mu'azu et al. (2023) augmented slope stability prediction by merging fuzzy logic with ANN optimized using the Teaching-Learning-Based Optimization (TLBO) algorithm. Gula et al. (2022) delved into various optimization schemes to enhance the performance of the ANFIS in slope stability prediction through a water cycle algorithm. These pioneering efforts, along with those of Mahmoodzadeh et al. (2022), who proposed a Gaussian process regression (GPR) model, and Jamalnia et al. (2021), who explored data-driven surrogate models using RF regressors, collectively contribute to the evolving landscape of slope stability assessment.

Furthermore, studies by Liu et al. (2021), Wang et al. (2021), Wei et al. (2019), and Moayedi et al. (2019) have introduced innovative methodologies ranging from reliability analysis combined with deterministic approaches such as online sequential extreme learning machine (OS-ELM), hybrid GA-MLP, GA-SVM models and particle swarm optimization (PSO)-ANN for shallow strip footing safety factor approximation, integration of groundwater level predictive models with slope stability analysis for rainfall threshold determination.

Through their collective efforts, these studies not only deepen our understanding of slope stability prediction but also offer practical insights and implications for geotechnical engineering and risk management practices.

Key findings from the survey of material available in the open literature

Table 6 shows the comparative analysis of several ML algorithms applied for FOS prediction based on RMSE. Figure 9 illustrates the findings presented by the authors for FOS prediction.

Table 6. Literature review			
Author	ML Method/technique	Input Variables	RMSE
Chen et al., (2023) [110]	Digital Twinning based CNN	ϕ , c , H , β	0.0759
Soranzo et al., (2023) [111]	CNN	ρ , c , ϕ	0.455
Mu'azu et al., (2023) [112]	ANN-TLBO	C_u , β , b/B	0.4958
Gula et al., (2022) [113]	WCA-ANFIS	C_u , β , w , b/B	0.3619
Mahmoodzadeh et al., (2022) [114]	GPR	c , β , H , γ	0.1372
Jamalnia et al., (2021) [115]	RF	c , ϕ , γ	0.05
Liu et al., (2021) [116]	OS-ELM	c , ϕ	0.0664
Wang et al., (2021) [117]	GA-MLP	β , b/B , F_y and C_u	0.107
Wei et al., (2019) [118]	GA-SVM	c , ϕ , γ	0.043
Moayedi et al., (2019) [119]	PSO-ANN	C_u , β , w , b/B	0.0157

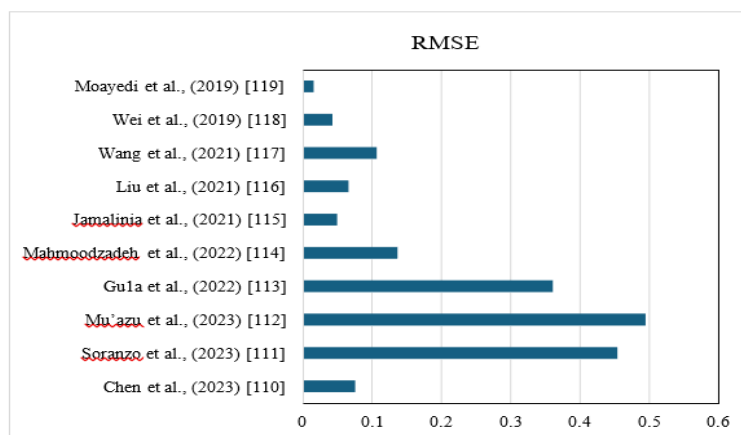


Figure 9. Findings presented by the Authors

(iv) Based on Mean Absolute Error (MAE)

Recent advancements in slope stability assessment have seen the emergence of innovative methodologies and techniques aimed at improving predictive accuracy and efficiency. Saikrishna macharyulu et al. (2024) present a pioneering approach utilizing a multi-objective PSO (MPSO) RF-SVR model for reinforced soil slope stability assessment, showcasing enhanced predictive capabilities. Xu et al. (2023) introduce an ensemble learning approach, employing a stacking strategy and multiple ML models to predict the FOS with superior performance. Bai et al. (2022) contribute to the field by investigating the efficacy of ML models in predicting slope safety factors, providing valuable insights for risk management in geotechnical engineering contexts.

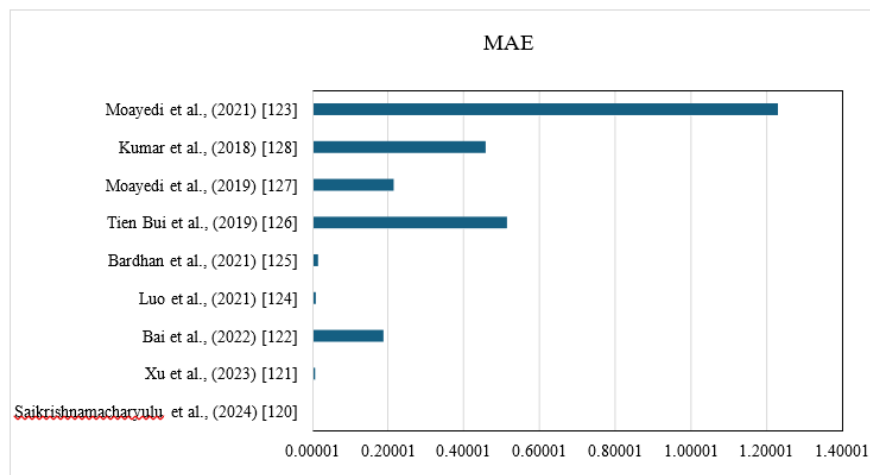
Innovative metaheuristic techniques are also introduced to enhance conventional methods in slope stability prediction. Moayedi et al. (2021) introduced Harris Hawks' optimization (HHO) as a metaheuristic technique to improve the performance of conventional MLP methods, showing significant accuracy improvements. Similarly, Luo et al. (2021) proposed a hybrid intelligent technique, PSO-cubist algorithm (PSO-CA), for predicting slope safety factors, surpassing other models and offering a promising solution for addressing geotechnical engineering instability issues. Bardhan et al. (2021) contributed to infrastructure projects by employing a Bi-directional Extreme Learning Machine (Bi-ELM) for predicting the FoS in seismic conditions for railway embankments, offering a simple yet effective computational approach for slope stability prediction. Tien Bui et al. (2019) and Moayedi et al. (2019) further enhanced predictive techniques by evaluating various ML-based methods, highlighting the efficiency of MLP and RF for similar slope stability problems. Finally, Kumar et al. (2018) developed a neural network model for slope stability computation, demonstrating its efficacy in accurately predicting the FOS and showcasing its potential for enhancing geotechnical engineering projects requiring slope stability analysis.

Key findings from the survey of material available in the open literature

Table 7 shows the comparative analysis of several ML algorithms applied for FOS prediction based on MAE. Figure 10 illustrates the findings presented by the authors for FOS prediction.

Table 7. Literature review

Author	ML Method/technique	Input Variables	MAE
Saikrishnamacharyulu et al. (2024) [120]	al., RF-SVR-MOPSO	c, ϕ , β , NL, Slope(ratio), Bar inclination	0.00129
Xu et al., (2023) [121]	stacking ensemble learning	Rainfall, RWL, GWL, ds, dd	0.0071
Bai et al., (2022) [122]	ANN	H, β , ρ , c, ϕ , r_u	0.1882
Moayedi et al., (2021) [123]	HHO-ANN	β , w, P, S _s	1.233
Luo et al., (2021) [124]	PSO-CA	H, β , ϕ , c, γ	0.009
Bardhan et al., (2021) [125]	Bi-ELM	μ	0.0150
Tien Bui et al., (2019) [126]	MLP	C _u , β , b/B, w	0.5155
Moayedi et al., (2019) [127]	RF	C _u , β , b/B, w	0.2152
Kumar et al., (2018) [128]	ANN	depth factor, cot β , ϕ	0.459

**Figure 10. Findings presented by the Author****4. Discussion**

The systematic review focuses on analyzing various ML techniques for slope stability assessment and prediction. The authors highlight several methods employed for predicting FOS, a critical parameter in slope stability analysis. The studies proposed by various authors methods utilize different techniques such as FEM, LEM, Empirical methods, Deep Learning, etc. to obtain FOS. Input variables for these models include parameters like soil density (ρ), cohesion (c), friction angle (ϕ), slope height (H), slope angle (β), and unit weight of soil (γ), among others. The performance of these

methods is evaluated based on various metrics, including accuracy, R^2 , RMSE, and MAE.

Noteworthy performances emerge across different evaluation metrics, demonstrating the efficacy of various ML techniques in slope stability analysis. Models employing Deep Learning, such as CNN, presented by Azmoon et al., (2021) and GRANN, presented by Deris et al., (2021), demonstrated high accuracy of 99.71% and 99.99%, respectively. Additionally, the techniques such as VO-ENSM, ANN-adam, and EO-MLP proposed by Ahmad et al., (2024), Pandey et al., (2022) and Foong et al., (2022) respectively exhibited high R^2 values, indicating robust predictive capability. Moreover, methods like PSO-ANN and GA-SVM suggested by Moayedi et al., (2019) and Wei et al., (2019) demonstrated low RMSE, signifying accurate predictions, while RF-SVR-MOPSO and PSO-CA methods utilized by Saikrishnamacharyulu et al., (2024) and Luo et al., (2021) showcases very low MAE values, highlighting their precision in predicting FOS.

This systematic review underscores the effectiveness of ML techniques in slope stability analysis, with various methods showing promising results across different evaluation metrics. These advancements contribute significantly to enhancing safety and reliability in engineering practices and infrastructure development.

5. Conclusion and Future Scope

The systematic review conducted in the present study emphasises the increasing significance of ML techniques in tackling the intricate and demanding task of slope stability analysis. The traditional deterministic and numerical methods have their limitations in capturing the inherent uncertainties and nonlinearities involved in slope failure mechanisms. ML algorithms have demonstrated their potential to overcome these limitations by leveraging data-driven approaches and learning from historical data. The review has shown that various ML techniques, such as ANN, SVM, MLP, and ensemble methods, have been successfully applied to slope stability assessment and prediction. These techniques have proven to be effective in handling large datasets, accounting for multiple contributing factors, and providing accurate and reliable predictions of slope failure or stability.

Additionally, the combination of ML techniques with other advanced methods, such as ANN-adam, EO-MLP, PSO-ANN, RF-SVR-MOPSO, etc., has enhanced the overall process of slope stability assessment. This systematic review has demonstrated the significant potential of ML techniques in enhancing slope stability assessment and prediction, leading to improved safety measures, risk mitigation strategies, and reliable decision-making processes in various engineering and geotechnical applications.

Further research and development in this area can explore the integration of advanced ML algorithms, such as reinforcement learning and ensemble methods, to enhance predictive accuracy and robustness. Moreover, there is potential for incorporating additional data sources, such as remote sensing imagery and real-time monitoring data, to improve model performance and enable proactive hazard management. Collaborative efforts between researchers, engineers, and stakeholders could foster innovation and facilitate the adoption of ML-driven approaches in practical engineering applications, ultimately contributing to safer and more reliable infrastructure development globally.

Notations

ρ	density	b/B	setbackdistance/ratio	D_t	Tensilecrackdepth
c	Cohesion	w_s	Soilweight	D_s	Slidingsurfacesdepth
ϕ	Frictionangle	Y	Young'smodulus	D_m	miningdepth
β	Slopeangle	ν	Poisson'sratio	d_s	surfacedisplacement
H	Slopeheight	E	Elasticmodulus	d_d	deep displacement
ru	Pressureratio	F_y	appliedslopestresses	GWL	GroundWaterLevel
γ	unitweight	S_m	Slopematerial	RWL	ReservoirWaterLevel
N_L	Layernumber	R_d	Rainfallduration	S_s	soilstrength
C_u	Undrainedcohesive strength	R_i	Rainfallintensity	P,	positionofrigid foundation

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