

An In-Depth Study of Artificial Intelligence Applications in Slope Stability Assessment of Mining Sites

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Abstract: *The stability of mine slopes is a critical aspect of open-pit mining operations, as slope failure can result in severe economic, environmental, and human losses. In recent years, Artificial Intelligence (AI) has emerged as a powerful tool for enhancing the accuracy and efficiency of slope stability assessments. This study presents a comprehensive review and deep analysis of AI-based approaches applied to slope stability assessment in mining areas. This study presents the first comprehensive and in-depth review focusing specifically on AI-based approaches applied to slope stability assessment in mining areas, highlighting their strengths and weaknesses. An in-depth analysis was adopted, focusing on peer-reviewed publications from 2010 to 2025, retrieved from databases such as Scopus, Google Scholar, and Web of Science. The selected studies were categorized into two main groups based on the type of AI techniques used: machine learning models and deep learning and optimization algorithms. The study reveals that AI models, particularly hybrid and deep learning approaches, outperform traditional deterministic methods in predicting slope failures, especially when dealing with complex, nonlinear geotechnical data. The integration of geospatial technologies with AI further enhances real-time monitoring and decision-making capabilities. These findings provide valuable insights for mining engineers and researchers, supporting the development of intelligent, data-driven systems for safer and more sustainable slope management in mining operations.*

Keywords: *Artificial intelligence, AI, slope stability, mine*

1. Introduction

In surface mining operations, particularly in open-pit and strip mines, slope stability assessment plays a vital role in ensuring operational safety and minimizing both human and economic losses. Slope failures in such environments can cause serious damage to mining infrastructure, environmental degradation, and even fatal accidents. Therefore, accurate evaluation of slope stability is essential in maintaining sustainable mining practices (Rachmad, 2015). Slope stability can be assessed by a UAV (Tsachouridis, Pavloudakis, Sachpazis, & Tsioukas, 2025), multi-criteria decision making methods (Shademan Khakestar, Hassani, Moarefvand, & Madani, 2016), numerical and limit equilibrium methods (Ataei & Bodaghabadi, 2008), three-dimensional rock mass modeling (Morales, Panthi, & Botsialas, 2019), improved Set Pair Analysis Method (X. Yang, Hao, Ma, & Li, 2021), etc. These approaches have been widely adopted due to their simplicity and established theoretical basis. However, they are often constrained by the assumptions made about the geological conditions, limited capacity to capture non-linear interactions between multiple geotechnical parameters, and their sensitivity to the quality and quantity of input data (Denisa, Tuhut, Simion, Raul, & Manea, 2024; Javid, Zarkesh, Boroumand, & Al-Fawa'reh, 2025). In recent years, Artificial Intelligence has been increasingly applied to slope stability assessment in mining areas. Compared with traditional geotechnical models, AI can handle large, heterogeneous, and sometimes incomplete datasets while capturing complex nonlinear relationships among slope factors. This makes AI a promising tool for open-pit mines, where data sparsity and uncertainty often limit conventional methods. However, current studies remain fragmented, with differences in algorithms, input variables, and validation approaches. A focused review is therefore needed to synthesize progress, highlight strengths and weaknesses, and identify future research directions.

In recent years, the rapid advancement of Artificial Intelligence (AI) has introduced promising alternatives for slope stability prediction. AI approaches, particularly Machine Learning (ML) and Deep

Learning (DL) models, have demonstrated high capability in analyzing large, complex datasets and modeling non-linear relationships among various influencing factors (Hasan, Al-Fawa'reh, Madelatparvar, & Fakhralmobasheri, 2025; Oumaima, Saâd, Abdessamad, & Amina, 2024). Techniques such as Artificial Neural Networks, Support Vector Machines (SVM), Random Forests (RF), and hybrid models integrated with optimization algorithms have shown better performance in predicting slope behavior than traditional statistical methods (Ghosh, 2023; Imam et al., 2023; Sahoo & Tripathy, 2025). Additionally, the integration of AI with IoT-based sensor networks allows for real-time monitoring and early-warning systems, further enhancing safety and proactive risk management in mines (Ramezani & Tafazoli, 2020; Saleem, 2025).

Several review articles have attempted to synthesize the application of AI in mining or geotechnical engineering. For instance, (Rachmad, 2015) emphasized the strategic role of AI in modern mining management, highlighting its potential in risk reduction and efficiency enhancement. (Saleem, 2025) conducted a broader review on AI and automation in mining, including safety management and predictive modeling applications. (Ramezani & Tafazoli, 2020) discussed AI's application in automating routine decisions in mining machinery, but did not go deeply into slope failure prediction. Besides, some studies have focused more on AI applications for mine slope stability assessment. While (Le Roux, Sepehri, Khaksar, & Murray, 2025) presented a comprehensive analysis of slope stability monitoring techniques and tools for open-pit mining, (Arif et al., 2025) conducted a review of machine learning methods for predicting rock slope stability, (Bui, Bui, & Nguyen, 2020) provided an overview of artificial intelligence's uses in geological engineering and mining, (S. Singh & D. Chakravarty, 2023) implemented a comprehensive mine study on using advanced machine learning for slope stability analysis in non-homogeneous conditions. Additionally, (Qi & Tang, 2018) analyzed the slope stability prediction utilizing combined machine learning and metaheuristic techniques. However, none of these studies have focused specifically on a deep comparative analysis of AI models applied to slope stability assessment in mining areas, nor have they classified the models based on methodology, input data, and deployment context

Although many AI applications for slope prediction exist, a comprehensive synthesis specifically focused on mining slopes is still lacking. Most prior works have addressed generic landslide problems or emphasized algorithm development without connecting it closely to mining scenarios. Additionally, there is a need to evaluate model performance comparatively, explore the integration with real-time data systems, and assess generalizability and interpretability across different mining environments. To address these gaps, this study aims to systematically analyze the application of artificial intelligence techniques in slope stability assessment, identify the strengths and limitations of different model categories, and highlight existing research gaps while outlining future trends and opportunities in this field

2. Methodology

2.1 Review Design and Approach

This review follows a systematic literature analysis methodology to synthesize and evaluate the current state of Artificial Intelligence (AI) applications in slope stability assessment within mining environments. The methodology adopted in this study follows a structured multi-step process, as illustrated in Figure 1. The process includes (1) Literature collection; (2) Initial screening; (3) Full-Text review; (4) Final selection of studies; (5) Classification of studies; (6) Analytical evaluation; (7) Synthesis and interpretation.

2.2. Data Sources and Search Strategy

Relevant academic publications were collected from reputable scientific databases including Google Scholar, Scopus, Web of Science, and ScienceDirect. Keywords and search strings were carefully defined to retrieve studies related to slope stability and AI-based modeling in mining, using combinations of terms as Table 1. Search results were filtered by title, abstract, and keywords for initial relevance. Snowballing from the reference lists of key studies was also applied to capture additional papers.

Tab. 1. Search Terms Used in Literature Retrieval

Search Category	Search Terms / Keywords
Key Concept 1: Slope Stability	"Slope stability" OR "slope failure" OR "slope deformation" OR "dump slope" OR "open-pit slope"
Key Concept 2: Artificial Intelligence	"Artificial intelligence" OR "machine learning" OR "deep learning" OR "AI" OR "neural networks"
Application Context	"Mining" OR "open-pit mining" OR "mine slope" OR

Search Category	Search Terms / Keywords
	“tailings dam” OR “waste dump”
Modeling Techniques	“Support vector machine” OR “decision tree” OR “random forest” OR “convolutional neural network” OR “ANN” OR “BPNN”
Monitoring & Prediction	“Real-time monitoring” OR “predictive modeling” OR “early warning” OR “IoT-based slope monitoring”
Combined Search Strings	- “Slope stability” AND “machine learning” AND “mining” - “Open-pit” AND “neural network” AND “slope failure” - “AI” AND “dump slope” AND “predictive model”

2.3. Inclusion and Exclusion Criteria

The selection of studies was based on strict inclusion and exclusion criteria to ensure scientific rigor and thematic relevance.

Inclusion criteria includes (1) written in English; (2) Published between 2010 and 2025; (3) Peer-reviewed articles from reputable journals indexed in Scopus, Web of Science, or Google Scholar; (4) Focused on slope stability assessment in mining areas (e.g., open-pit, waste dumps, tailings dams); (5) Involving AI/ML/DL techniques applied for modeling, prediction, or monitoring purposes; (6) Providing sufficient methodological detail on AI model structure and evaluation.

Exclusion Criteria include (1) Non-English publications; (2) Articles published before 2010 or outside the defined time range; (3) Conference abstracts, technical reports, dissertations, or opinion papers lacking peer-review; (4) Studies using only conventional deterministic or probabilistic methods (e.g., FEM, LEM) without AI integration; (5) Applications focused solely on natural landslides or non-mining environments

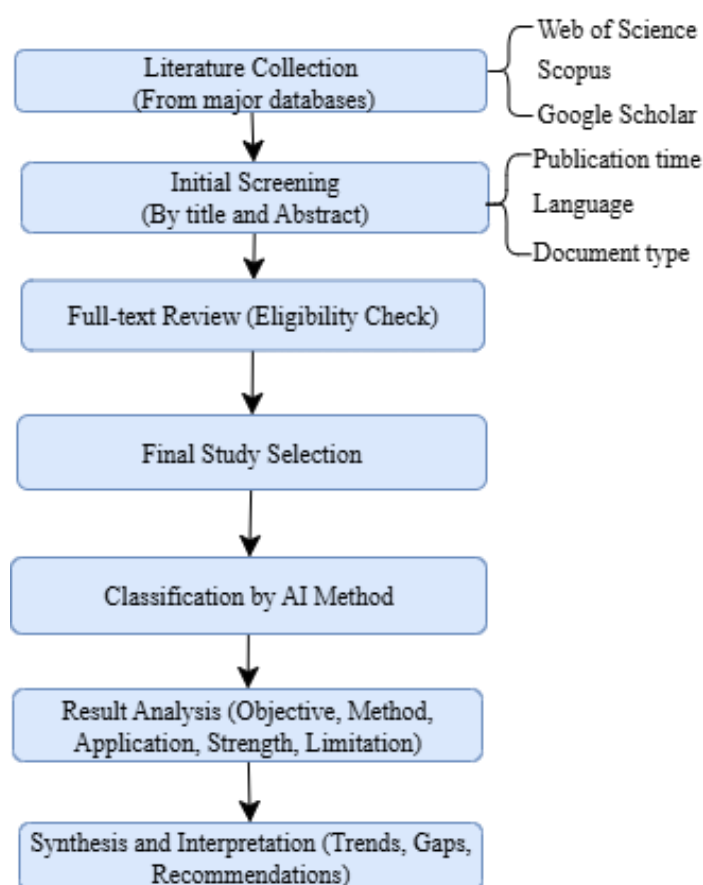


Fig. 1. Flowchart of research

2.4 Study Selection and Data Extraction

After applying the criteria, an initial pool of over 100 publications was reduced to 32 core studies. These were reviewed in full text and evaluated for: Type of AI algorithm used; Input parameters and geotechnical context; Data source (laboratory, field, or remote sensing); Application domain (e.g., pit wall, waste dump, tailings dam); Real-time integration, explainability, and innovation.

The selected studies were categorized into methodological groups based on the AI technique. A comparative matrix was constructed to analyze and compare model architectures, data sources, performance outcomes, and the scope of application. This structured framework allowed for identifying research trends, strengths and weaknesses, and unexplored opportunities in the field.

3. Application of Artificial Intelligence in slope stability assessment of mining areas

3.1. Prediction and assessment of slope stability in mining areas using machine learning models

Assessment and prediction of slope stability in mining areas is an important challenge in the fields of geotechnical engineering and mining. In recent years, ML models have been widely applied to improve the accuracy of predicting the Factor of Safety (FoS), landslide risk, and classifying slope stability. This section analyzes some representative studies using traditional ML techniques (such as Decision Tree, Random Forest, Support Vector Machine, k-Nearest Neighbors, Gradient Boosting, etc.), artificial neural networks, as well as hybrid models, monotonic constraints, and surrogate models. These studies mainly focus on open-pit mining, dump slopes, and diverse environmental conditions.

In order to analyze slope stability, some studies used Artificial Neural Networks. (Rahul, Khandelwal, Rai, & Shrivastva, 2015) evaluated the stability of a dump slope in a coal mine using a backpropagation artificial neural network. Input parameters included cohesion, friction angle, slope angle, and unit weight. The ANN was trained on site-specific datasets and showed high prediction accuracy for factor of safety (FoS), confirming its suitability for real-time applications. Besides, criteria of safety prediction for slope stability were offered in (Jing et al., 2025). The authors proposed a model combining principal component analysis (PCA) for dimensionality reduction with backpropagation neural networks (BPNN) to predict slope safety in a mining area in Guangdong. The reduced input space led to faster training and less overfitting, while BPNN captured nonlinear relationships effectively. In another study, (Idris, 2022) applied Artificial Neural Network models to evaluate the slope stability of a laterite borrow pit under a probabilistic framework. By integrating geotechnical parameters such as cohesion, internal friction angle, and unit weight, the ANN was trained to estimate the Factor of Safety (FoS). The probabilistic assessment provided a more comprehensive understanding of slope failure risks, accounting for input variability. The results highlighted the reliability of ANN models in handling uncertainty in slope stability analysis.

In addition to ANN, Tree-based and Ensemble models are also utilized in several research. (Singh & Chakravarty, 2023) employed Random Forest (RF) and XGBoost models to predict slope stability while analyzing the relative importance of input features. Feature selection improved model interpretability and emphasized the dominant influence of slope angle and unit weight on FoS. The ensemble methods outperformed conventional decision trees. In another study, a bagging-based ensemble was developed using decision trees and k-NN classifiers to enhance slope stability prediction. The ensemble model demonstrated robustness in scenarios with noisy or sparse data, and showed improved performance compared to standalone learners in terms of both classification accuracy and generalization (Nguyen, Tinh, & Tien, 2021). Though details were limited, (Amini, Khoshrou, & Iranmanesh, 2024) applied AI models to analyze the stability of open-pit mine walls. The authors likely used decision-tree-based models (e.g., CART or RF) based on the structure of the data. AI applications were shown to improve efficiency over traditional geotechnical computations. Additionally, (Das et al., 2022) proposed a machine learning-enabled IoT framework for monitoring and enhancing slope stability in open-cast mining operations. Real-time sensor data is processed using ML algorithms (e.g., decision trees) to predict instability trends. The system aims to improve preventive decision-making by providing continuous slope health assessment. Also, (Yang, Hou, Tao, Peng, & Shi, 2015) focused on the design and deployment of a remote real-time monitoring system for a sliding slope body in the Luoshan mining area. It uses sensor-based data acquisition (displacement, rainfall) and likely incorporates basic predictive models to evaluate slope stability evolution. The emphasis is on timely warning and engineering response. In another study, an AI-based system for real-time detection and early warning of geotechnical instabilities in mining slopes was presented in (Contador Villegas, Huenchulao Catalán, Oliva Miranda, Dubournais Donoso, & Gallardo Arriagada, 2021). It integrated sensor networks with traditional machine learning algorithms to assess slope behavior

dynamically. The system emphasized automation, data integration, and rapid response for risk mitigation in open-pit environments. In addition, (Ayache, Santos, & Silva, 2023) applied a decision tree algorithm to classify the stability conditions of mine slopes based on key geotechnical parameters. The model is trained using data such as slope angle, cohesion, and internal friction angle, and then used to predict whether a slope is stable or unstable. The decision tree approach offers high interpretability and allows for transparent decision rules, making it suitable for practical mine slope safety assessments.

Other approach, Hybrid / Surrogate / Dimensionality Reduction Models, also employed in various publications. (Gladious, Paul, & Mukhopadhyay, 2025) focused on predicting key geotechnical input parameters (such as cohesion and internal friction angle) using ML models trained on borehole and laboratory data from iron ore mines in high precipitation zones. These predicted parameters were then used in slope stability analysis, effectively making ML a surrogate for part of the geotechnical process. Besides, to predict slope stability more reliably, (Ragam et al., 2024) proposed an ensemble-based hybrid model that combined multiple ML techniques such as stacking, voting. The hybrid approach enhanced prediction performance and addressed overfitting problems seen in single models. Additionally, (Y. Yang, Ji, Gao, & Liang, 2025) developed surrogate models using support vector regression and Kriging techniques to simulate slope behavior under different sampling scenarios. The goal was to reduce computational effort in numerical modeling while maintaining predictive accuracy. Also for the purpose of estimating slope stability, (Pei & Qiu, 2024) introduced monotonicity constraints into ML algorithms (such as XGBoost), ensuring that input-output relationships adhere to geotechnical logic (e.g., increased cohesion should not reduce stability). The constrained models showed better interpretability and reliability for engineering decisions.

To assess the accuracy, the stability prediction of natural and artificial slopes needs to be conducted using various machine learning algorithms. (Karir et al., 2022) evaluated multiple ML classifiers—Support Vector Machines, Random Forest, k-NN—on datasets from natural and anthropogenic slopes. Results highlighted that RF achieved the highest accuracy, while k-NN suffered in cases with high dimensionality. Similarly, (Mahmoodzadeh et al., 2022) conducted a detailed comparison of several ML models for predicting slope FoS. Data normalization, model selection, and hyperparameter tuning were discussed. Gradient boosting and SVM offered the most consistent results across test cases. Furthermore, the robustness and generalization ability of ML algorithms (including decision tree, RF, and ANN) across multiple datasets were systematically assessed in (Tiwari, Das, & Mohanty, 2025). Performance was evaluated using accuracy, F1-score, and AUC metrics. The work provides guidance for model selection based on data properties.

On the other hand, a conceptual paper discussing how AI can be integrated into mining operations, with slope stability as a key case. It reviewed ML capabilities without diving into specific models or datasets. It set the stage for more detailed applications (Jayanthu, Mahapatra, Sahu, & Pati, 2024). Besides, (Li, 2021) developed a classification model to assign stability ratings to mine rock slopes. Though it claims to use AI, the methodology and dataset are not clearly specified. The study showed potential but lacked technical transparency. However, in the study of (Baghbani & Baumgartl, 2024), the authors combined numerical simulation results (e.g., from FLAC or PLAXIS) with machine learning models to build a reliability framework. This hybrid approach improved predictive robustness but was not used for real-time monitoring. Also uses a general ML application, (GUPTA, SHARMA, & Singh, 2022) applied unspecified AI models to dump slope data. The lack of algorithmic detail limits its reproducibility, though the results showed promise in replacing traditional slope analysis methods. The approach of this study is quite general and lacks technical details.

The studies reviewed on machine learning applications in slope stability prediction were classified into five methodological subgroups: (A) Artificial Neural Networks, (B) Tree-based and Ensemble Models, (C) Hybrid/Surrogate/Constrained Models, (D) Comparative/Benchmarking Studies, and (E) General or Unspecified AI/ML Approaches. Table 2 lists the studies, their objective, methods, advantages, and limitations.

Tab. 2. Studies on machine learning applications in predicting and evaluating slope stability of mining areas

References	Objective	Methods	Advantages	Limitations
A. Artificial Neural Networks				
(Rahul et al., 2015)	To predict dump slope stability using ANN	Artificial Neural Network	- Capable of modeling complex nonlinear relationships. - High predictive accuracy with sufficient and clean datasets.	- Often considered "black-box" models with limited interpretability. - Prone to overfitting without careful architecture design or regularization.
(Jing et al., 2025)	To estimate slope stability via factor of safety prediction using PCA and BPNN	PCA and Backpropagation Neural Network		
(Idris, 2022)	Evaluate slope stability under uncertainty using an ANN for predicting the Factor of Safety (FoS).	Artificial Neural Network in a probabilistic framework		
B. Tree-based and Ensemble Models				
(Nguyen et al., 2021)	Improve slope stability prediction using ensemble learning	Bagging + Decision Tree + k-NN	- High interpretability (especially with Decision Trees). - Perform well with noisy, imbalanced, or incomplete datasets. - Robustness is enhanced through ensemble methods such as bagging or boosting.	- May introduce bias in highly imbalanced classification tasks if not calibrated. - Require careful tuning when dealing with continuous variables.
(S. K. Singh & D. Chakravarty, 2023)	Evaluate feature importance in predicting dump slope failures	Random Forest / XGBoost + feature importance		
(Amini et al., 2024)	Assess the slope stability of open-pit mine walls using intelligent algorithms	Likely tree-based ML (e.g., Decision Tree, RF)		
(Contador Villegas et al., 2021)	Implement a real-time AI-based early warning system for mining slope instability	Sensor network + real-time ML classification		
(Yang et al., 2015)	Real-time remote monitoring of slope body using sensors + AI	IoT sensors + simple ML-based prediction (likely decision tree)		
(Das et al., 2022)	Enhance slope stability monitoring in open-cast mines by integrating real-time sensor data (IoT) with ML techniques for prediction and early warning.	Machine Learning models (likely Decision Trees or SVM) integrated with IoT sensor network for real-time data collection and processing.		
(Ayache et al., 2023)	To classify mine slope stability using a decision tree model trained on geotechnical input features.	Decision Tree (DT)		

References	Objective	Methods	Advantages	Limitations
C. Hybrid/Surrogate/Dimensionality Reduction Models				
(Gladious et al., 2025)	predict key geotechnical input parameters affecting slope stability	Traditional ML regression (supports surrogate modeling)	- Incorporate domain knowledge (e.g., geotechnical logic through monotonic constraints). - Surrogate models reduce computation time compared to full-scale numerical models. - Hybrid models combine strengths from multiple ML algorithms for improved accuracy.	- Increased model complexity makes them harder to deploy in real-time systems. - Require advanced understanding of both ML techniques and geotechnical behavior.
(Yang et al., 2025)	To build and test surrogate models with different data sampling schemes	Surrogate model + ML regression		
(Ragam et al., 2024)	To enhance slope stability prediction with ensemble ML techniques	Ensemble models (e.g., stacking, RF)		
(Pei & Qiu, 2024)	To apply monotonic-constrained ML for slope stability estimation	Monotonic ML (e.g., constrained XGBoost)		
D. Comparative Studies / Benchmarking				
(Karir et al., 2022)	To compare ML methods for predicting slope stability	Comparative ML study (SVM, RF, etc.)	- Provide objective evaluations of ML model performance on specific tasks. - Essential for selecting suitable models based on data characteristics.	- Typically, do not introduce new algorithmic innovations. - Offer less direct guidance for deployment or operationalization.
(Mahmoozadeh et al., 2022)	To benchmark different ML algorithms in predicting slope safety factor	ML algorithm comparison		
(Tiwari et al., 2025)	To systematically assess ML models for slope classification and regression	Benchmarking of classification/regression models		
E. General AI/ML Applications (Unspecified Methods)				
(Jayanthu et al., 2024)	To explore the use of AI for enhancing slope stability assessment	General AI/ML overview	- Offer conceptual overviews and potential directions for AI use in mining. - Valuable for scoping studies or early-stage research planning.	- Often lack algorithmic specificity and reproducibility. - Limited applicability without detailed methodological implementation.
(Li, 2021)	To develop an AI-based system for rating slope stability	AI classification (algorithm not specified)		
(Baghbani & Baumgartl, 2024)	To integrate AI and numerical methods for slope reliability analysis	Numerical modeling + unspecified ML		
(Gupta et al., 2022)	To assess dump slope stability using AI-based models	General ML application		

3.2. Application of deep learning and optimization algorithms in slope stability analysis

This section presents a comprehensive synthesis of studies focusing on the application of Deep Learning and Metaheuristic Optimization Algorithms in the analysis of slope stability in mining areas. Slope failures pose significant safety, economic, and environmental risks in open-pit mining. Traditional methods, such as limit equilibrium or finite element analysis, while effective, often struggle with data nonlinearity, dynamic conditions, and real-time predictions. To address these challenges, researchers have increasingly applied advanced artificial intelligence approaches, notably deep learning models (e.g., DNN, CNN, RBFNN) and metaheuristic optimization techniques (e.g., Particle Swarm Optimization (PSO), Imperialist

Competitive Algorithm (ICA), Brainstorm Optimization (BSO), Harris Hawks Optimization (HHO), Bayesian Optimization). These models enhance the accuracy, adaptability, and generalizability of slope stability prediction systems, especially when large datasets or field monitoring data are available.

(Wang, Zhang, & Wang, 2023) focused on the development of a deep neural network (DNN) model to predict the factor of safety (FoS) of slopes in mining environments. The authors trained the DNN on a dataset comprising key geotechnical parameters such as cohesion, internal friction angle, slope angle, and unit weight. The aim was to build a model that could learn the complex nonlinear relationships among these variables and generate reliable FoS predictions. The results showed that the DNN model outperformed traditional statistical techniques, suggesting strong potential for deep learning in slope stability analysis. Additionally, (Nguyen, Bui, Choi, & Topal, 2024) proposed a hybrid model that combines a Radial Basis Function Neural Network (RBFNN) with the Imperialist Competitive Algorithm (ICA). The RBFNN serves as the core predictive engine, while the ICA is used to optimize its parameters and structure. The model was applied to a dataset of slope cases to predict the factor of safety. This hybrid approach was designed to address the sensitivity of neural networks to initial weights and structure by allowing global optimization. Results indicated a significant improvement in prediction accuracy and convergence speed compared to standalone models. Besides, In order to improve model training, (Shang et al., 2022) builds upon the RBFNN architecture by integrating the Brainstorm Optimization (BSO) algorithm. The main objective was to enhance the robustness and generalization of the model for predicting slope stability under varying geological conditions. The BSO-RBFNN was tested against several benchmark datasets and achieved superior accuracy and stability in learning. The approach demonstrated the power of combining nature-inspired optimization with neural networks for high-performance geotechnical modeling. Still using DNN, (Zhang et al., 2022) explored the use of a deep neural network (DNN) optimized by the Harris Hawks Optimization (HHO) algorithm to estimate the internal friction angle of clay soils, a key input in slope stability models. By accurately predicting this parameter from other measurable soil properties, the model contributes to more reliable geotechnical design. The HHO algorithm was employed to optimize the hyperparameters of the DNN, resulting in faster convergence and improved accuracy. This study demonstrates the potential of AI in substituting expensive and time-consuming lab tests. In another study, the authors introduced a one-dimensional convolutional neural network (1D-CNN) model enhanced by Bayesian Optimization to analyze slope stability. The CNN architecture was used to extract features from time-series sensor data, making it particularly suitable for monitoring slope deformation over time. Bayesian Optimization was applied to fine-tune model hyperparameters, balancing performance and computational efficiency. The approach proved highly effective in capturing temporal trends and predicting slope behavior in a real-world mining context, suggesting practical applicability in early-warning systems.

(Jingfeng & Xing, 2025) proposed an integrated framework combining geospatial technologies (ArcGIS, GPS, Remote Sensing), the 3S system, and artificial intelligence (AI) algorithms for assessing the stability of rock slopes in mining areas. The model utilizes multi-source data, including topographic surveys, remote sensing imagery, and real-time monitoring inputs, to train machine learning models for predicting the factor of safety (FoS). The results demonstrate that this integrated approach significantly improves prediction accuracy, enhances real-time adaptability, and offers practical value in mine slope management.

Tab. 3. Research on applying deep learning and optimization algorithms in slope stability analysis of mining areas

Refernces	Objective	Methods	Strengths	Limitations
A. Deep Learning (DNN, CNN, RBFNN, etc.)				
(Wang et al., 2023)	Estimate the slope stability coefficient using deep learning techniques	Deep Neural Network (DNN)	- High accuracy and nonlinearity handling	- Data-hungry, especially high-quality labeled datasets
(Nguyen et al., 2024)	Develop a robust slope prediction model using hybrid neural networks	Radial Basis Function Neural Network and Imperialist	- Automatic feature learning - Good for large datasets.	- Models lack interpretability, making it difficult to explain results

Refernces	Objective	Methods	Strengths	Limitations
		Competitive Algorithm		- Requires significant processing power for training
(Shang et al., 2022)	Apply RBFNN with optimization to enhance slope stability prediction	RBFNN and Brainstorm Optimization		
(Zhang et al., 2022)	Estimate soil parameters for slope analysis using deep learning	Deep Neural Network and Harris Hawks Optimization		
(Lyu et al., 2024)	Use a 1D Convolutional Neural Network to predict slope stability	1D-CNN and Bayesian Optimization		
B. Metaheuristics / Optimization Techniques (PSO, GA, ICA, etc.)				
(Bui, Nguyen, et al., 2020)	Predict slope failure in open-pit mines using a hybrid ML model	Decision Tree and Evolutionary Algorithm	- Effective in Complex Problem Spaces	- High Computational Complexity
(Luo, Bui, Nguyen, & Moayedi, 2021)	Analyze slope stability using a metaheuristic-based model	Particle Swarm Optimization and Cellular Automata	- Improved Prediction Accuracy Through Hybridization - Flexibility and Adaptability	- Model Transparency and Interpretability - Sensitivity to Parameter Settings
C. Hybrid/Surrogate				
(Chand et al., 2025)	Predict the stability of mine tailings dams using an AI risk assessment tool	AI models for risk classification and prediction (likely ANN or ensemble)	- High Practical Applicability	- Dependence on Non-Standard or Noisy Data
(Zhou et al., 2025)	Improve prediction by combining incremental learning and knowledge extraction	Incremental Bayesian learning + NLP / Text mining	- Integration of Expert Knowledge and Field Data - Adaptive Learning and Time-Based Updates	- Implementation Complexity - Limited Generalizability
(Du et al., 2019)	Predict slope deformation using real-world field sensor data and ML	Supervised ML (possibly RF, SVM) applied to time-series data		- Lack of Algorithmic Transparency
(Jingfeng & Xing, 2025)	integrate geospatial technologies (3S) and AI to assess slope stability more effectively and dynamically	Hybrid approach using GIS + Remote Sensing + GPS (3S) + Machine Learning models in ArcGIS environment		

3.3. Dissussion and future trends in AI-based slope stability assessment for mining areas

From the above analysis results, quantitative performance indicators including accuracy, Area Under the Curve (AUC) and Root Mean Square Error (RMSE) determined in recent studies for different types of artificial intelligence models applied to slope stability assessment in mining areas are summarized in Table 4. The table classifies the methods into five main groups: Artificial Neural Networks, Tree-based and Ensemble Models, Hybrid/Surrogate/Constrained Models, Deep Learning approaches, and Metaheuristic Optimization Algorithms. Each group is associated with typical data types used for training and the specific mining application domains such as dump slopes, open-pit mine walls, and tailings dams.

Tab. 4. Quantitative summary table in slope stability assessment of mining areas

Algorithm Group	Accuracy / AUC / RMSE	Data Type	Application Domain
Artificial Neural Networks	Accuracy: 85-95% (classification); RMSE varies (FoS prediction)	Geotechnical site-specific parameters; Probabilistic inputs	Dump slopes, borrow pits
Tree-based and Ensemble Models (Random Forest, XGBoost, Bagging)	Accuracy: 88-98% (classification); AUC high (0.9+ typical)	Noisy, imbalanced, sparse field data	Open-pit mine walls, dump slopes
Hybrid/Surrogate/Constrained Models	Improved accuracy over single models; RMSE reduced by 10-20% vs baseline	Borehole, laboratory, combined data	Open-pit mines, tailings dams
Deep Learning (DNN, CNN, RBFNN)	Accuracy: 90-98%; RMSE lower than traditional ML; good nonlinear handling	Large labeled datasets, time-series sensor data	Slopes in open-pit mines, dynamic monitoring
Metaheuristic Optimization Algorithms (PSO, ICA, BSO, HHO)	Enhanced prediction accuracy by 5-15% over base ML; computationally intensive	Complex geotechnical datasets	Open-pit mines, mine walls

From the table, it is evident that Deep Learning (DNN, CNN, RBFNN) consistently achieves the highest accuracy levels (typically 90-98%) with lower RMSE values compared to more traditional machine learning models. This reflects their superior capability in capturing complex nonlinear relationships, particularly when large, labeled datasets or time-series sensor data are available. However, these models are data-hungry and require substantial computational resources. Tree-based and Ensemble models such as Random Forest and XGBoost show strong and robust performance with accuracies in the range of 88-98%, even when handling noisy, imbalanced, or sparse field data common in mining environments. Their interpretability and efficiency make them suitable for deployment in practical settings like open-pit mine walls and dump slopes. The Artificial Neural Networks group, including variants integrated with dimensionality reduction like PCA, demonstrate good classification accuracy (approximately 85-95%) and handle probabilistic inputs effectively, making them a reliable choice for sites like borrow pits and dump slopes. Their limitations mainly include concerns about interpretability and vulnerability to overfitting without careful model design. Hybrid, surrogate, and constrained models improve predictive accuracy by combining strengths of multiple ML methods or integrating domain-specific geotechnical logic. These methods reduce computational costs by acting as surrogates for numerical simulations and show RMSE reductions of 10-20% compared to baseline models. They are typically applied in open-pit mines and tailings dam stability assessments. Finally, Metaheuristic optimization algorithms like Particle Swarm Optimization and Imperialist Competitive Algorithm enhance base ML model performance by 5-15%, primarily in complex problem spaces such as mine walls. Despite their improved accuracy and adaptability, they demand high computational effort and careful sensitivity analysis.

The analysis results showed that, artificial intelligence methods, including machine learning and deep learning, have been widely applied in slope stability assessment in open mining areas with many outstanding advantages and disadvantages. The advantage of AI methods is the ability to effectively handle large, complex data sets and non-linear relationships between various geotechnical parameters. Models such as Artificial Neural Networks, Decision Trees, Random Forests, and hybrid models that incorporate optimization algorithms all provide more accurate slope stability predictions than traditional methods based on assumptions and deterministic calculations. In addition, AI also supports rapid, automated assessments and has the ability to be applied in real time when integrated with IoT sensor technology, thereby improving the ability to monitor and warn of the risk of slope instability. Ensemble models such as Random Forest also have the advantage of recognizing the importance of input factors, helping to increase the interpretability and reliability for geotechnical engineers.

However, AI approaches also have some limitations. First, deep learning models in particular require large amounts of high-quality data for training, which is not always feasible in mining environments with limited or heterogeneous data. Second, many AI models, especially neural networks, are often considered “black boxes” due to their complexity and difficulty in explaining, making it difficult to convince technical

experts and make decisions based on model results. In addition, setting up, optimizing hyperparameters, and deploying hybrid or optimized models also require specialized knowledge and can be computationally intensive. Finally, some studies lack diverse experimental data, standardized datasets, and have not fully exploited real-time monitoring data, limiting the broad and general applicability of AI models.

To overcome these challenges, the development and curation of standardized, high-quality datasets tailored for mining slope stability is essential. Employing advanced data preprocessing techniques such as data cleaning, missing data imputation, and balancing can improve training dataset quality. Incorporating Explainable AI (XAI) techniques, including interpretable models and post hoc explainability tools, enhances the transparency and usability of predictions by geotechnical engineers. The application of dimensionality reduction and feature selection methods can reduce model complexity and improve prediction robustness while accelerating training times. Integrating AI models with real-time data acquisition systems like IoT sensor networks and GIS-based platforms allows continuous monitoring and early warning capabilities. Implementing online learning or incremental model updating strategies enables adaptation to changing site conditions.

Furthermore, expanding field validations across diverse mining sites and geological conditions improves the robustness and transferability of AI models. Collaborative multidisciplinary efforts combining data scientists, geotechnical experts, and mining engineers facilitate the development of practical and user-friendly AI tools. Capacity building and training are also crucial for effective AI adoption in mining operations. By addressing these factors, AI methods can achieve greater reliability, transparency, and operational value in slope stability assessment, fostering safer and more sustainable mining practices.

The future of artificial intelligence in slope stability assessment is moving toward more robust, interpretable, and real-time predictive systems, addressing the critical challenges of safety and risk mitigation in mining operations. Traditional models like ANN, while powerful, are being gradually replaced or complemented by hybrid systems that combine multiple machine learning techniques or integrate AI with domain-specific constraints. This shift aims to balance predictive accuracy with transparency and interpretability, allowing geotechnical engineers to better trust and understand the model outputs. Besides, Random Forests, XGBoost, and other ensemble models have gained popularity due to their robust performance across diverse datasets and ability to identify feature importance. These methods have shown high adaptability in mining environments where data quality can be variable and heterogeneous. Additionally, a growing number of studies incorporate real-time sensor data and Internet of Things (IoT) frameworks into slope stability analysis. This integration enables continuous monitoring and early warning systems, facilitating proactive responses to geotechnical risks. For example, ML algorithms process live data streams to forecast instability trends, as seen in studies (Contador Villegas et al., 2021; Das et al., 2022; X. Yang et al., 2015). Moreover, surrogate models and methods like Principal Component Analysis (PCA) are increasingly used to reduce computation cost while maintaining accuracy, especially when replacing time-consuming numerical simulations. These approaches support faster decision-making and operational deployment. On the other hand, Deep neural networks (DNNs), convolutional neural networks (CNNs), and metaheuristic optimization techniques such as PSO, ICA, and HHO are being explored to improve predictive capacity under nonlinear and dynamic conditions. These techniques are especially useful when working with large or time-series datasets from field monitoring. Some models have introduced monotonicity constraints to ensure that the learned relationships comply with geotechnical logic (e.g., increasing cohesion should not reduce slope stability). This makes the models more reliable and acceptable in engineering applications, as demonstrated in the study of (Pei & Qiu, 2024). As the variety of available ML models expands, there is a parallel rise in benchmarking research that evaluates their performance under various data conditions. This is crucial for identifying the best-fit model based on specific site characteristics and available data. While many models achieve high accuracy on localized datasets, future research should focus on enhancing the generalizability and transferability of AI models to different mining contexts. This requires larger datasets, standardized protocols, and open-access databases.

4. Conclusion

This study has conducted a thorough and systematic investigation of recent applications of Artificial Intelligence in the assessment of slope stability within mining areas. By employing a structured literature analysis of studies published over the last 15 years, the research categorized existing works into two main groups based on AI methodology: machine learning models and deep learning and optimization algorithms. The study utilized clearly defined selection criteria, including publication quality, language (English), relevance to the mining sector, and AI application. The results demonstrate that AI techniques—particularly

hybrid models combining machine learning with geospatial technologies and optimization algorithms—have significantly improved the accuracy, flexibility, and practicality of slope stability prediction. These methods show strong performance in handling complex, nonlinear geotechnical data and in enabling real-time monitoring.

This study not only highlights the strengths and limitations of current AI-based approaches but also identifies key research gaps, such as limited field validation, lack of standardized datasets, and underutilization of real-time monitoring data. Future research should focus on developing standardized benchmarking datasets, enhancing model transparency and interpretability, and expanding the integration of real-time, multisource data to build more robust, adaptive, and intelligent slope stability assessment systems in mining operations.

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