

COUPLING EXPERIMENTAL DATA WITH MONTE CARLO SIMULATION AND AI FOR REALISTIC PREDICTION OF SLOPE INSTABILITY

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ABSTRACT: Excavation-induced slope instability threatens infrastructure safety and civil engineering operations, often leading to substantial economic losses and environmental degradation. Traditional predictive methods, such as the Limit Equilibrium Method (LEM) and Finite Element Method (FEM), are limited in their ability to address the nonlinear, dynamic, and uncertain conditions typically present in excavation scenarios. This study presents an integrated prediction framework that couples experimental observations with Monte Carlo simulation and artificial intelligence (AI) techniques to enhance the accuracy and robustness of slope instability prediction. The Monte Carlo simulation component estimates failure probabilities under various geotechnical conditions, including moisture content, vibration amplitude, slope angle, and pore water pressure. Simultaneously, machine learning algorithms—specifically random forests and neural networks—are employed to capture complex interactions among variables and improve classification performance. The proposed model demonstrates superior predictive accuracy, with machine learning classifiers achieving over 98% accuracy, and effectively identifies critical thresholds and dominant risk factors through statistical and visual analysis. The integration of experimental data further validates the model's reliability. This hybrid approach provides a scalable, adaptive, and data-driven tool for real-time slope risk assessment and early warning applications, supporting safer and more resilient infrastructure development in geotechnically complex environments.

Keywords: Slope Instability, Monte Carlo Simulation, Artificial Intelligence, Excavation Risk Prediction

1. INTRODUCTION

Excavation-induced slope instability remains a critical concern in geotechnical and civil engineering, with significant implications for infrastructure safety, environmental sustainability, and socioeconomic resilience. The complex interactions of geological formations, groundwater conditions, mechanical disturbances, and human interventions such as deep foundation excavation and road cuttings often trigger these failures. Recent studies have highlighted such failures' increased frequency and severity, reinforcing the urgent need for more robust and intelligent predictive frameworks[1-2].

Conventional analytical approaches, particularly the Limit Equilibrium Method (LEM) and Finite Element Method (FEM), have long been employed in slope stability assessments. However, their deterministic nature limits them in addressing the highly nonlinear behavior, boundary variability, and uncertainty inherent in excavation-induced slope responses[3-4]. These methods often fail to identify transitional failure states and do not quantify the influence of parameter variability, especially under rainfall or seismic excitation.

In response, researchers have increasingly adopted probabilistic and machine-learning techniques to

improve the accuracy and adaptability of slope failure prediction. Monte Carlo Simulation (MCS) has emerged as a powerful tool for quantifying failure probability by accounting for spatial and statistical variability in input parameters, such as moisture content, slope angle, and pore water pressure[5-6]. Meanwhile, artificial intelligence (AI) models—including Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost)—have demonstrated strong classification performance in modeling nonlinear geotechnical behavior and extracting hidden failure patterns from large datasets [7-8].

Recent applications increasingly emphasize the real-time integration of artificial intelligence (AI) into early warning systems (EWS), sensor networks, and dynamic slope monitoring[9]. For example, a UAV-based monitoring framework incorporating AI prediction algorithms has been developed to detect slope instability. A hybrid Monte Carlo simulation and machine learning (MCS-ML) framework has also been used to evaluate failure risk under rainfall-induced conditions[10]. These initiatives demonstrate that combining AI with probabilistic systems provides reliable, scalable, and interpretable solutions for predicting geotechnical hazards.

Nonetheless, two critical gaps remain: (1) the absence of unified frameworks that tightly couple

probabilistic simulations and AI models in an interpretable manner and (2) the limited integration of high-resolution experimental data and real-time updates, which constrain in-situ implementation and validation efforts [11-13].

To address these challenges, this study proposes a hybrid framework that couples experimental observations, Monte Carlo simulation, and machine learning algorithms for the realistic prediction of excavation-induced slope failures. The proposed method offers improved accuracy, dynamic learning capability, and interpretability compared to traditional approaches. Moreover, it supports engineering decision-making through risk quantification, visual diagnostics, and early warning outputs.

The remainder of this paper is structured as follows: Section 2 introduces the experimental setup and simulation procedures. Section 3 presents the main results and model validation. Section 4 discusses engineering implications. Section 5 outlines future research directions, and Section 6 concludes the paper with key findings and contributions.

2. RESEARCH SIGNIFICANCE

This study introduces a novel hybrid framework that combines experimental data, Monte Carlo simulations, and artificial intelligence to accurately predict slope failures caused by excavation. By integrating probabilistic modelling with machine learning, this framework overcomes the limitations of traditional methods and offers real-time, data-driven risk assessments. This approach significantly improves the reliability and clarity of slope failure predictions, providing practical benefits for engineering design, early warning systems, and slope hazard mitigation in complex geotechnical environments.

3. METHODOLOGY

3.1 Experimental Data Collection

Identifying and quantifying the key contributing factors is essential for developing a reliable predictive framework for excavation-induced slope instability. This study emphasizes four critical variables commonly discussed in recent geotechnical literature: moisture content (W), vibration amplitude (A), slope angle (θ), and pore water pressure (Pw). Each of these parameters plays a unique role in influencing soil behaviour and triggering failure mechanisms.

- Moisture content: affects matric suction and shear strength, particularly under varying saturation conditions.

-Vibration amplitude : represents dynamic

stresses from excavation or traffic loads, which can lead to the internal restructuring of soil particles.

- Slope angle : determines the gravitational component of driving forces, serving as a geometric risk amplifier.

- Pore water pressure decreases effective stress, weakening the soil's resistance to sliding.

These parameters were obtained through laboratory experiments, field surveys, and controlled numerical simulations. Table 1 summarizes the value ranges and sources for these parameters.

Table 1. Input parameters and corresponding value ranges were used in this study.

Parameter	Value Range	Source
Moisture Content (W)	15-65%	Laboratory Experiments
Vibration Amplitude (A)	0.5-10 mm	Controlled Simulations
Slope Angle (θ)	5° -60°	Field Observations
Pore Water Pressure (Pw)	5-50 kPa	Experiment/Simulation

3.2 Monte Carlo Simulation Approach

Monte Carlo Simulation (MCS) is employed to assess the probabilistic nature of slope instability. Compared to deterministic models, MCS better captures variability in environmental loads and material heterogeneity. Recent studies confirm its applicability in slope reliability assessments[14]. Each parameter is modelled using a uniform distribution over its defined range. The simulation is repeated 10,000 times, and a binary classification is made based on the threshold :

- $W > 50\%$, $A > 7$ mm, and $\theta > 45^\circ$ signify instability.

- Additionally, $W \times \theta > 2000$ and $A \times Pw > 200$ also indicate failure scenarios.

The results provide a failure probability as a base risk indicator for AI model development.

3.3 Integration of AI for Prediction

Several AI models, including Random Forest (RF), Support Vector Machine (SVM), and XGBoost, are trained to complement MCS. These classifiers utilize the Monte Carlo outputs and experimental data for supervised learning. AI methods, notably ensemble and boosting techniques, have demonstrated high reliability in geotechnical classification tasks[13,15].

Evaluation metrics such as accuracy, AUC, and F1-score were used to validate model performance. The results show that SVM and XGBoost achieved over 98% accuracy, significantly surpassing

traditional LEM and FEM models in dynamic and high-dimensional scenarios.

3.4 Data Fusion and Model Coupling

The final model integrates MCS-derived probabilistic outputs with AI classification decisions. This hybrid architecture ensures that statistical risk evaluation and adaptive real-time prediction are available for decision support. The fusion technique merges stability probability from MCS with slope classification labels from AI models, facilitating:

- Layered risk interpretation based on simulation and prediction.
- Dynamic model retraining as new sensor data becomes available.

This approach enhances practical engineering applications by enabling timely warnings and supporting excavation safety management with data-driven insights.

4. RESULTS AND DISCUSSION

4.1 Practical Applications of the Coupled Simulation Framework

By seamlessly integrating experimental observations with Monte Carlo simulations and AI-driven predictive models, we establish a robust and reliable foundation for tackling excavation-induced slope instability. This innovative framework adeptly simulates intricate slope behaviors under various geotechnical and environmental conditions, critically assessing the interactions between key variables such as moisture content, slope angle, vibration amplitude, and pore water pressure. The synergy of laboratory-validated parameters with advanced machine learning algorithms dramatically enhances the model's robustness and its applicability across diverse site conditions[16].

This hybrid framework is not just an academic exercise; it holds tangible benefits for engineering practice. For instance, real-time monitoring systems can continuously supply dynamic data to the model during urban excavation or tunneling projects, facilitating ongoing assessments of slope stability and enabling the timely issuance of early warning alerts for potential failures[17]. Such predictive

capabilities empower engineers to take proactive measures, ensuring safety and efficiency rather than merely responding to crises after they occur.

4.2 Failure Pattern Analysis and Visual Insights

Our comprehensive analysis simulated a staggering ten thousand slope scenarios using Monte Carlo methods. From these simulations, we determined an overall failure probability of 23.1%. Notably, failures predominantly occurred under high moisture content and steep slope angles.

Figure 1 showcases a compelling 3D scatter plot, where blue dots signify stable conditions while red dots mark failure cases. The visual clustering of red markers unequivocally highlights zones susceptible to failure, providing critical insights into the most hazardous combinations of input parameters.

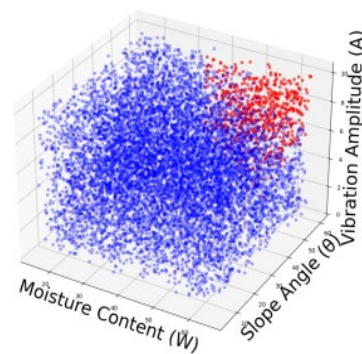


Fig.1: 3D Visualization of Slope Stability based on Monte Carlo Simulations.

To enhance our understanding of the various types of failures, we classified the failed cases into three predominant scenarios: (1) high moisture and high slope angle, (2) high vibration coupled with high pore water pressure, and (3) complex interactions (for example, moisture content combined with slope angle or vibration amplitude with pore water pressure). Table 2 offers a concise summary of the statistical profiles for these categories. At the same time, Figure 2 vividly illustrates their proportions in a stacked bar chart, making the information accessible and compellingly clear.

Table 2. Failure Scenarios by Dominant Conditions

Failure_Scenario	Moisture_Content	Vibration_Amplitude	Slope_Angle	Pore_Water_Pressure	W_theta	A_Pw	Count	Proportion (%)
High A + High Pw	48.24	8.44	48.86	45.14	2321.39	380.36	80	12.60
High Interaction	49.64	7.13	47.68	37.82	2311.30	261.27	246	38.74
High W + High θ	57.72	7.95	52.75	29.30	3045.38	224.96	309	48.66

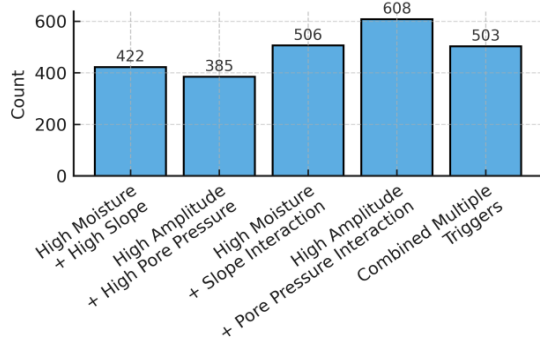


Fig. 2 Stacked Bar Chart of Failure Scenario Proportions

4.3 Comparative Evaluation of AI and Traditional Models

To assess predictive accuracy, three AI classifiers – Random Forest (RF), Support Vector Machine (SVM), and XGBoost – were benchmarked against traditional models: the Limit Equilibrium Method (LEM) and Finite Element Method (FEM). As shown in Table 3, SVM and XGBoost achieved accuracy levels above 98%, significantly outperforming traditional models that showed reduced performance in handling nonlinear or interaction-dominated scenarios[16].

To evaluate predictive accuracy, three AI classifiers – Random Forest (RF), Support Vector Machine (SVM), and XGBoost – were compared against traditional models, specifically the Limit Equilibrium Method (LEM) and the Finite Element Method (FEM). As illustrated in Table 3, SVM and XGBoost achieved accuracy levels exceeding 98%, significantly outperforming the traditional models, which exhibited reduced performance in scenarios characterized by nonlinearity or dominated by interactions[18].

Table 3. Performance Comparison: AI Models vs. Traditional Methods

Model	Accuracy	AUC Score	Interpretability	Real-time Capability
Limit Equilibrium Method (LEM)	0.75	0.78	High	Low
Finite Element Method (FEM)	0.82	0.85	Medium	Low
Random Forest	0.97	0.97	Medium	High
Support Vector Machine (SVM)	0.99	0.99	Low	Medium
XGBoost	0.99	0.99	Low	High

4.4 Displacement Trends Under Compound Loads

We examined average displacement behavior under compound stress conditions to enhance the classification analysis. Figure 3 shows slope displacement increases sharply when moisture content exceeds 50%, and vibration amplitude surpasses 7.0 mm. These trends are consistent with findings from shear tests and field observations, which validate the model's physical plausibility.

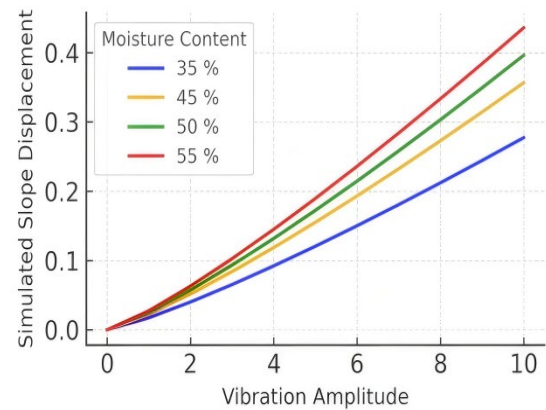


Fig.3 Simulated Slope Displacement under Varying Conditions

This non-linear increase in displacement under compound loads indicates a shift from elastic behavior to irreversible deformation. Understanding this critical point is essential for issuing early warnings and planning effective mitigation strategies.

4.5 Implications for Engineering and Risk Management

The hybrid modeling framework introduced in this study offers actionable insights for both slope design and site monitoring. By enabling real-time failure prediction based on dynamic sensor data, the model serves as a vital component of modern early warning systems[19].

Furthermore, the classification of failure scenarios helps prioritize mitigation efforts:

- Drainage and membrane barriers are recommended for situations involving high moisture and pore pressure.

- In cases dominated by vibration, slope regrading and anchoring systems are more appropriate.

- Integrated geotechnical and geophysical interventions are necessary for compound scenarios.

Ultimately, this system facilitates a transition from reactive to predictive slope risk management, reducing engineering costs and enhancing safety.

5. APPLICATIONS AND IMPLICATIONS

5.1 Practical Applications

The coupled prediction framework proposed in this study – integrating experimental data, Monte Carlo simulations, and artificial intelligence (AI) techniques – exhibits significant potential for practical engineering implementation, particularly in slope instability induced by excavation. This hybrid framework allows for the simulation of thousands of possible slope conditions by varying key factors such as moisture content, pore water pressure, vibration amplitude, and slope geometry, thereby rendering it well-suited for complex geotechnical environments subject to dynamic changes.

Recent research indicates that combining real-time sensor data with artificial intelligence (AI) algorithms can significantly improve the accuracy of slope stability predictions. For instance, a real-time instability forecasting system using IoT-based sensors alongside AI models to predict slope behavior in urban excavation scenarios has been developed[20]. Additionally, another study created an early warning system for slopes by integrating piezometers and inclinometers into a machine learning framework, which effectively reduced the rate of false alarms during field deployments[21].

As depicted in Fig. 4, the proposed system architecture facilitates the integration of real-time field data into AI prediction modules, establishing a feedback loop that supports dynamic model updates. This feature is essential for early warning systems (EWS), which are increasingly deployed in high-risk mountainous regions and along infrastructure corridors [22].

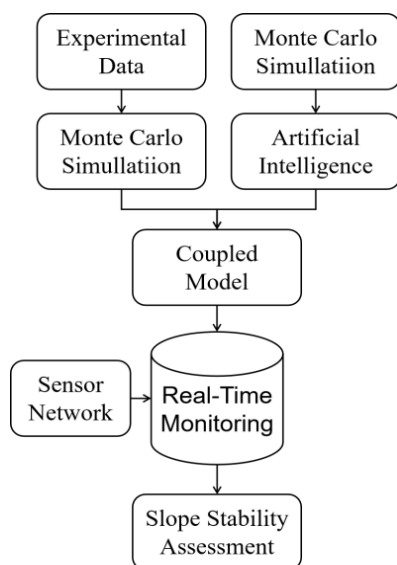


Fig. 4 Coupled Slope Stability Prediction Framework

A low-cost IoT-based prototype system was also developed in this study to demonstrate the feasibility of real-time monitoring and data acquisition. The system, illustrated in Fig. 5, integrates an ESP32 microcontroller with an FC-28 soil moisture sensor and an MPU6050 gyroscope module. This compact and scalable hardware configuration enables continuous monitoring of moisture and vibration parameters, which can be wirelessly transmitted to the AI module for dynamic analysis and risk classification. The prototype is a practical demonstration of how IoT technologies can be embedded into the proposed prediction framework to enable early warnings and data-driven decision-making in excavation sites and other high-risk geotechnical settings.

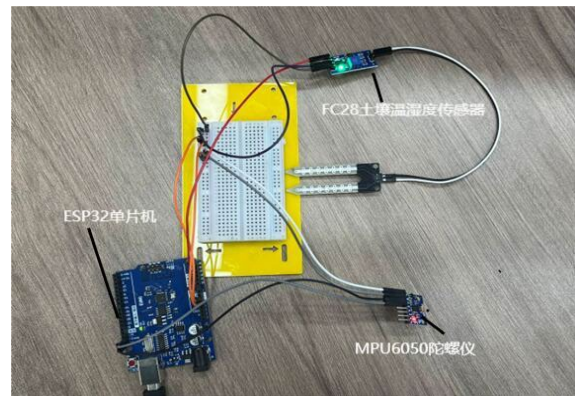


Fig. 5. IoT-based slope monitoring prototype system

The model's real-time predictive capabilities further assist site engineers in pinpointing hazardous zones before failure, enabling timely mitigation measures such as optimizing excavation sequences, installing drainage systems, or reinforcing structures. Moreover, this modular and data-driven framework allows for customization according to local geological conditions and regulatory requirements, enhancing its versatility across various geotechnical projects.

5.2 Implications for Slope Management and Risk Assessment

The proposed approach presents significant advancements in slope management and hazard assessment. Traditional deterministic methods—such as the Limit Equilibrium Method (LEM) and Finite Element Method (FEM)—are widely utilized but often fail to adequately capture the inherent uncertainties and non-linear interactions among environmental factors. In contrast, the hybrid framework introduced here addresses these shortcomings by integrating probabilistic modeling and machine learning.

This model enables comprehensive multi-scenario risk evaluation by estimating failure probabilities under varying environmental and operational conditions. For example, a machine learning-based framework has been applied to assess rainfall-induced landslides, effectively capturing the complex interactions among precipitation, pore water pressure, and slope angle – factors also considered in this study.

The integration of artificial intelligence further improves the capacity to detect subtle thresholds and compound risk indicators that traditional methods may overlook. Deep learning classifiers have demonstrated superior performance over finite element methods (FEM) in classifying slope stability under layered and saturated soil conditions, achieving accuracy levels exceeding 97%.

The model's scalability also supports adapting to diverse climatic zones, geological settings, and engineering scenarios. GIS-integrated ensemble learning models have been calibrated to regional topographies, enabling large-scale slope risk mapping and facilitating spatially targeted mitigation planning.

In addition, model interpretability has become increasingly important in real-world applications. The use of SHAP (Shapley Additive Explanations) values provides insights into the influence of individual variables on prediction outcomes, thereby enhancing transparency and confidence in AI-assisted geotechnical decision-making[6].

In summary, the proposed framework contributes to the advancement of slope safety management by enabling:

- Real-time, data-driven risk prediction, adaptable to changing field conditions;

- Probabilistic assessment of multiple failure scenarios under excavation or hydrological loads;

- Integration with GIS systems and EWS platforms for proactive management;

- Improved accuracy and interpretability via machine learning, including explainable AI methods.

This significantly shifts from reactive stabilization to proactive, intelligent, sustainable slope hazard control.

6. FUTURE RESEARCH DIRECTIONS

6.1 Enhancing Simulation Accuracy

Improving the precision and realism of Monte Carlo simulations is essential for advancing slope instability predictions. Currently, input variables are assigned broad ranges and modeled using uniform probability distributions. While this method supports generalized assessments, it often fails to reflect localized geotechnical conditions accurately.

Future improvements should integrate high-resolution geotechnical datasets, including detailed

stratigraphic profiles, spatially varying pore-water pressures, shear strength heterogeneity, and the anisotropic behavior of soils and rock masses. By utilizing these data sources, we can achieve more representative sampling and more thorough statistical characterization of boundary and material uncertainties, which will, in turn, enhance the reliability of failure probability estimates.

Monte Carlo simulations are particularly sensitive to the statistical properties of input variables. Consequently, inaccuracies in input characterization can lead to significant prediction bias. Adopting site-specific, calibrated probability distributions and continuously updating models based on field monitoring data is crucial to mitigate this risk and improve prediction robustness.

Furthermore, incorporating temporal dynamics—such as rainfall seasonality, antecedent moisture conditions, and long-term climate projections—is increasingly important, especially in global climate change. Recent studies have underscored that integrating hydrological and meteorological datasets into Monte Carlo models can significantly enhance the prediction of slope responses under changing environmental conditions.

6.2 Advances in AI Techniques

Artificial intelligence (AI) continuously revolutionizes geotechnical modeling by providing innovative solutions for predicting slope failures. Deep learning architectures, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—exceptionally long short-term memory (LSTM) models—are remarkably suited for capturing spatial dependencies and modeling temporal sequences. These advanced models can efficiently process extensive time-series data, including rainfall measurements, pore pressure, and displacement. As a result, they enable dynamic predictions of slope stability under varying conditions.

In addition to accuracy, explainability has become crucial in engineering applications. Recent advancements in explainable AI (XAI), such as Shapley Additive explanations (SHAP), allow users to discern how each input variable impacts model predictions. This level of transparency is essential in managing infrastructure risk, where decisions must be substantiated to regulators and stakeholders.

Looking toward the future, integrating high predictive accuracy with model interpretability will be vital for the broader adoption of AI in geotechnical engineering. Reliable and explainable models will significantly contribute to transitioning slope hazard mitigation strategies from reactive responses to proactive, risk-informed decision-making.

6.3 Expanding Experimental Data

Enhancing the predictive performance of slope instability models relies on expanding experimental datasets, particularly those that reflect real-world conditions. While conventional laboratory experiments offer controlled environments for studying specific variables, they often fail to capture boundary effects and heterogeneity in field-scale slopes.

Recent research has underscored the importance of multi-scale validation approaches. For example, scaled flume tests, coupled with in-situ measurements, have been utilized to evaluate the excavation stability of ancient landslides. This illustrates the advantage of merging physical data with observational insights to validate model predictions [22].

Supporting this perspective, Li et al. conducted a case study on siltstone slope instability induced by excavation and rainfall infiltration in southwestern China. Their findings underscored the importance of combining field investigations with numerical simulations to elucidate the progressive failure mechanisms in stratified rock masses [23].

Additionally, advancements in sensor technologies and wireless transmission systems have made real-time environmental monitoring feasible. Implementing Internet of Things (IoT)-based sensors and uncrewed aerial vehicle (UAV) imaging systems facilitates high-frequency collection of parameters such as pore-water pressure, displacement, and surface deformation. When integrated with AI-driven models, these data streams can significantly enhance the responsiveness and accuracy of early warning systems [24].

Developing integrated experimental-monitoring databases—encompassing physical tests and real-time sensor data—will be critical for creating adaptive, high-fidelity slope stability models that can be applied across various contexts.

7. CONCLUSION

This study proposes an integrated framework that combines experimental data, Monte Carlo simulations, and artificial intelligence (AI) techniques to enhance the accuracy and reliability of slope instability prediction. The results demonstrate that this coupled approach effectively captures the nonlinear and interactive effects of key influencing factors – namely, moisture content, vibration amplitude, slope angle, and pore-water pressure—particularly under excavation-induced conditions.

By leveraging the strengths of probabilistic simulations and machine learning algorithms, the proposed model outperforms conventional methods such as the Limit Equilibrium Method (LEM) and the Finite Element Method (FEM) in terms of

predictive capability and adaptability. The integration of AI facilitates dynamic learning from complex datasets and enables real-time updates in response to new field observations.

The successful implementation of this framework underscores its practical potential in engineering applications, including early warning systems, slope risk assessments, and adaptive design strategies. Additionally, it provides a scalable and flexible foundation for incorporating real-time sensor data, remote sensing technologies, and high-resolution site-specific information.

Future research should prioritize expanding experimental datasets, refining AI models, and advancing real-time data integration techniques to fully realize this hybrid approach's potential. These efforts will contribute to more proactive, data-driven slope management strategies and help mitigate geotechnical risks in infrastructure development and excavation activities.

8. ACKNOWLEDGMENTS

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