



Physics-guided ensemble machine learning framework for slope failure prediction

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Abstract

Purpose. This research aims to provide a physics-based ensemble machine learning framework that can reliably predict slope stability and distinguish stable from unstable slopes in static and seismic conditions. Standard analytical and numerical methods have significant processing costs and oversimplified assumptions that limit their usefulness.

Methods. The study analyzed 700 slope stability samples, including geotechnical and seismic factors such as slope height, slope angle, cohesion, internal friction angle, and peak ground acceleration. The proposed model now includes physics-based engineering elements, such as $\tan \phi$, c/H , and PGA/g , to account for geotechnical interactions. A linear meta-learner and Random Forest and Gradient Boosting regressors were used to develop a stacked ensemble framework. We assessed model strength and reliability.

Findings. The devised framework showcased exceptional prediction performance with an (R^2) of 0.982, a mean absolute error of 0.02 and a root mean square error of nearly 0.03. Cross-validation showed consistent generalization. Random Forests classified slope stability conditions with 97.4% accuracy. The most important parameters for slope stability predictions were the internal friction angle and cohesiveness. Furthermore, the inclusion of carefully crafted physics-based features demonstrably improved robustness, accuracy and consistency.

Originality. This work introduces a pioneering, combined framework that fuses the mechanics of geotechnical soil with ensemble machine learning techniques, enhancing both interpretability and the certainty of slope stability predictions.

Practical implications. The framework may support rapid, cost-effective, and interpretable preliminary geotechnical risk assessment and design screening. However, its use in slope monitoring or early-warning applications requires further field validation and integration with monitoring data.

Keywords: physics-guided machine learning; slope stability; factor of safety; ensemble learning; seismic loading

1. Introduction

Slope failures cause severe geotechnical and socio-economic consequences. In geotechnical engineering, slope failures are a recurring problem that often has disastrous consequences, including infrastructure damage, financial losses, and fatalities worldwide [1], [2]. For risk reduction and sustainable earth construction design, accurate slope stability prediction remains essential. Slope stability analysis has long been based on conventional techniques such as the Limit Equilibrium Method (LEM) and the Finite Element Method (FEM). However, these methods frequently fail to capture the nonlinear relationships between geotechnical and seismic characteristics, are computationally intensive, and require numerous simplifying assumptions [3], [4].

With data-driven capacities to simulate intricate, nonlinear interactions among soil parameters, geometry, and external stresses, machine learning (ML) has become a promising method for slope stability prediction in recent years [2],

[5]. Compared with conventional analytical models, machine learning methods such as Random Forest (RF), Gradient Boosting Regressor (GBR), Support Vector Regression (SVR), and Neural Networks have achieved high predictive accuracy. Despite these benefits, many current research studies rely solely on statistical or black-box methods that ignore physics consistency or the incorporation of geotechnical knowledge into the learning process, and as a result are not interpretable [6], [7].

To overcome these limitations, this study develops a Physics-Guided Ensemble Machine Learning Framework that incorporates geotechnical concepts into data-driven modeling. The approach leverages the resilience, feature handling, and generalization of both methods by combining Random Forest and Gradient Boosting Regressor within a stacked ensemble meta-learner. To improve physical interpretability, essential soil strength and seismic response characteristics are reflected in engineering features such as $\tan \phi$, c/H , and PGA/g [8]-[10]. The framework classifies slopes

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into stable or unstable states using a threshold of $FoS \geq 1.0$, in accordance with standard geotechnical safety requirements, and also provides regression-based predictions of the factor of safety (FoS) [11]-[14].

Predicting slope stability and failures remains a critical concern in geotechnical engineering, given the severe technical, environmental and socio-economic consequences of slope collapse [14]. Traditional limit-equilibrium and numerical methods provide rigorous solutions but are often computationally expensive, require detailed site-specific inputs, and rely on simplifying assumptions that may limit generalization [15]. In response, data-driven and machine learning (ML) approaches have gained increasing traction since 2020. ML methods facilitate the learning of nonlinear relationships among geotechnical parameters and failure outcomes, enabling faster, potentially more scalable assessment of slope stability [16].

A growing number of recent studies compare ML algorithms for predicting factors of safety (FoS) or for stability classification. For example [1], [17] review several studies on ML classifiers for slope stability and show that ensemble methods and hybrid models increasingly dominate performance. In another review [2], the strengths and weaknesses of ML models such as SVR, M5P, and ANN for FoS prediction are summarized, and interpretability and practical applicability are emphasized as key challenges. Several works apply ML to slope stability under seismic or spatial variability conditions [18], [19] demonstrates the use of ML surrogates for fast reliability analysis on anisotropic heterogeneous slopes, achieving a very large speed-up relative to Monte Carlo simulation. Pei et al. [5] propose knowledge-guided machine learning better to align ML predictions with physical behavior in slope stability. Zhang et al. [4] present a physics-guided neural network framework for 3D slope stability analysis. Several applied case studies focus on ensemble learning. For instance, the “Enhanced slope stability prediction using ensemble machine learning” by Yadav et al. [20] shows high precision in slope engineering using ensemble ML models. In the open-pit mining context, a recent study uses an ensemble ML approach (XGBoost-RF) to estimate FoS on field slopes with limited data. A comparison of empirical, numerical and ML techniques for road-cut slopes in mountainous terrain finds that RF, GBM and XGBoost outperform classical methods when field data are available. Beyond pure accuracy, interpretability is increasingly emphasized: study [21] integrates SHAP explanations with stacking ensemble learning for slope stability classification. Meanwhile, [21] review physics-informed machine learning (PIML) in geotechnical engineering and call for embedding domain knowledge directly into ML workflows. Finally, specialized models for circular-failure mode slopes [22] propose hybrid approaches combining ML algorithms with engineered features to improve reliability.

Existing Research Gaps: Despite these advances, literature still exhibits key gaps. First, while many studies apply ML, few ones systematically incorporate physics-consistent feature engineering (e.g., $\tan \phi$, c/H , seismic PGA/g). Second, although interpretability techniques (SHAP, permutation importance) are increasingly used, relatively few works couple interpretability with ensemble or hybrid models and demonstrate alignment of feature importance with geotechnical theory. Third, the classification of slope stability (stable

vs unstable) is less often integrated with FoS regression in a unified framework. Finally, applications of PIML (physics-informed machine learning) remain nascent in slope-stability literature compared to other geotechnical areas.

This paper addresses these gaps by proposing a physics-guided ensemble ML framework that:

- integrates geotechnical physics into feature engineering;
- employs a stacked ensemble (Random Forest + Gradient Boosting \rightarrow Linear meta-learner) for robust FoS regression and slope classification (stable/unstable);
- uses permutation-based interpretability to verify alignment with domain theory.

By doing so, it aims to combine high predictive accuracy, interpretability and field-deployment potential in a way that recent literature has not fully achieved.

2. Methodology

2.1. The required data for slope stability models

Limit Equilibrium Methods (LEMs) [7], Artificial Neural Networks (ANNs) [23]-[28], and the Finite Element Method (FEM) [25], [29] are among the most popular methods for slope stability analysis. These methods include empirical equations and limit analysis based on the lower and upper bound theorems. All the above approaches have drawbacks.

Limit equilibrium approaches cannot accurately reflect the stress on slip surfaces. Other approaches include Back-Propagation Neural Network (BPNN) [29]-[31]. Additionally, Support Vector Machine (SVM) [28], [32], Feedforward Neural Network (FFNN) [33], Chaotic CNN [32], Extreme Learning Machine (ELM) [29], and [34].

Extreme learning machine (ELM), particle swarm optimization (PSO), Least Squares Support Vector Classification (LS-SVC), functional networks (FNs), multivariate adaptive regression splines (MARS), genetic programming (MGGP), and LSSVM [35] are also popular methods.

Based on the full dataset from [8], which includes 700 samples with 6 input features and 1 target variable, a comprehensive machine learning (ML) analysis plan is proposed, tailored specifically for assessing slope stability.

2.2. Dataset overview

The problem addressed in this study is formulated as a regression task to predict the factor of safety (FoS) as a continuous indicator of slope stability. Based on the predicted FoS value, slope conditions are further classified into two categories: unstable slopes with $FoS < 1.0$ and stable slopes with $FoS \geq 1.0$, where higher FoS values indicate greater stability.

The dataset used in this study consists of 700 slope stability samples adopted from the published dataset of Asteris et al. [8], which was originally developed for slope stability classification under seismic conditions using tree-based intelligent techniques. Each sample includes geotechnical and seismic input variables, namely slope height (H), slope angle (β), cohesion (c), internal friction angle (ϕ), unit weight (γ), and peak ground acceleration (PGA) as shown in Table 1, with the factor of safety (FoS) used as the target output (Fig. 1). Therefore, the dataset used in this study was not newly collected from field investigations or newly generated by the authors through independent numerical simulations. Rather, the present work uses the published 700-sample dataset as the basis for developing and evaluating the proposed physics-guided ensemble machine learning framework.

Table 1. The slope variable, grouped by feature, description and type

Feature	Description	Type
H	Slope height, m	Numerical
β	Slope angle, degrees	
c	Cohesion, kPa	
ϕ	Internal friction angle, degrees	
γ	Unit weight, kN/m ³	
PGA	Peak ground acceleration, seismic load, ms ⁻²	
FoS	Factor of safety, target	

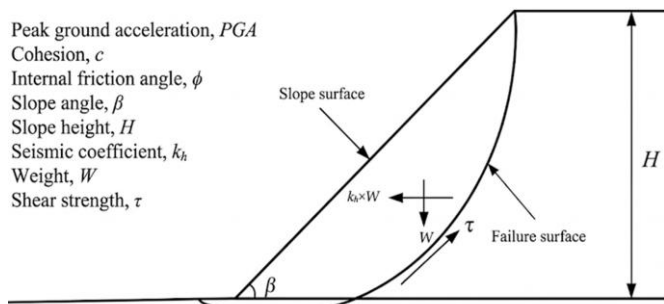


Figure 1. A generic limit equilibrium model for the simulated slope

There are no missing values in the dataset, so there will be no discrepancies in further analysis. It has its roots in a controlled parametric experiment, in which each input parameter (H , β , c , ϕ , and PGA) is varied over physically realistic domains to model a wide range of slope conditions. The methodology enables the successful modeling of stable/unstable slope conditions and enables the strong training and validation of machine learning (ML) processes.

The analysis of the data set performed through exploration analysis presents several trends of geotechnical parameters that remain consistent with theoretical assumptions:

The factor of safety (FoS) is more likely to do this as cohesion (c) and the internal friction angle (ϕ) increase, indicating improved shear strength and soil resistance.

On the other hand, FoS declines with increases in slope height (H), slope angle (β), and peak ground acceleration (PGA); thus, high slope heights, steepness, and seismic loading are intrinsically unstable.

Scatter plots and pairwise correlation tests indicate non-linear relationships, suggesting that simple linear models may not fully capture slope behavior.

Specifically, the interaction effects, i.e., ϕ (friction angle) vs. PGA (seismic loading), appear to significantly affect FoS, which underscores the need to introduce nonlinear machine learning models capable of accounting for these effects.

Overall, the EDA indicates that the dataset exhibits clearly defined geotechnical trends and is sufficiently diverse to support the development of predictive ML models for slope stability analysis.

The slope data used in this study were sourced from multiple sources as the testing dataset for machine learning algorithms developed [36]-[38]. The slope data for this study originated from multiple sources and served as the test dataset for machine learning algorithms taught; hence, it is not associated with a particular mining location [8].

The discussed methodologies encompass extreme learning machine (ELM) [39], particle swarm optimization (PSO) [40], least squares support vector classification (LS-SVC) [41], functional networks (FNs), multivariate

adaptive regression splines (MARS), multigene genetic programming (MGGP), and least squares support vector machine (LSSVM) [42].

The collection, which covers cohesive to granular soils under static and seismic stress situations, incorporates both field and simulated records that represent a broad range of slope geometries and material attributes. Data values were standardized within physically plausible boundaries H (5-50 m), β (20-60°), c (5-80 kPa), ϕ (20-45°), and PGA (0.05-0.6 g), consistent with typical ranges reported in recent geotechnical investigations to guarantee model generalization [5], [43]. It is possible to represent both stable (FoS \geq 1.0) and unstable (FoS $<$ 1.0) circumstances because the FoS values range from 0.5 to 2.5.

2.3. Machine learning models

The overall methodological workflow is shown in Figures 2 and 3. The proposed Physics-Guided Ensemble Machine Learning (PG-EML) framework integrates advanced ensemble learning techniques with geotechnical knowledge to predict the factor of safety (FoS) and classify slope stability conditions. As illustrated in Figure 2, the proposed PG-EML framework comprises five main phases: data collection and preprocessing, physics-guided feature engineering, ensemble model construction, model evaluation and interpretability, and output generation for predicted FoS and stability category.

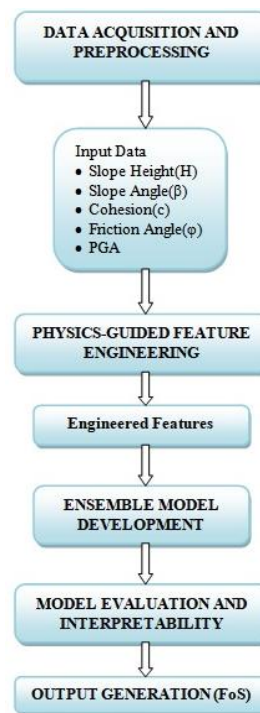


Figure 2. Model framework outline

The quality, diversity, and representativeness of the input data significantly impact the performance and reliability of any machine learning (ML) model. This study developed and assessed the suggested physics-guided ensemble learning framework (Fig. 3) using a curated dataset of 700 slope stability samples. Six basic geotechnical and geometric parameters, slope height (H), slope angle (β), cohesiveness (c), internal friction angle (ϕ), unit weight (γ), and peak ground acceleration (PGA), that are frequently employed in stability assessment, comprise the dataset.

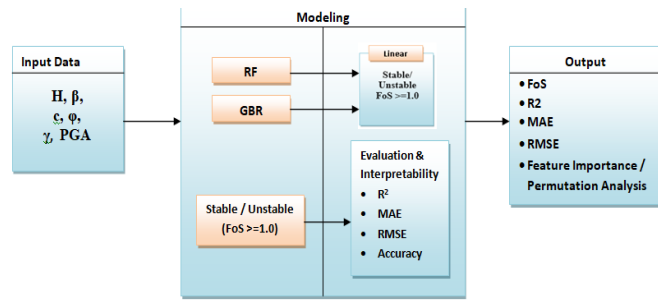


Figure 3. Overall framework of the proposed physics-guided ensemble machine learning model for slope stability prediction

The factor of safety (FoS), which measures the difference between driving and resisting forces operating on a slope, is the target variable.

To understand the links between the input factors and their impact on FoS, an exploratory study was conducted. According to the correlation matrix, slope height (H) and slope angle (β) have substantial negative correlations with FoS, but cohesion (c) and friction angle (ϕ) have positive correlations. These results are compatible with basic slope stability mechanics [2], [3], [12]. This finding indicates that increases in seismic acceleration reduce rock slope stability margins. The correlation between PGA and FoS confirms this trend and is consistent with pseudo – static seismic analysis that typically shows decreasing factors of safety as seismic accelerations increase.

While leveraging the predictive power of ensemble learning, incorporating physically meaningful features (such as $\tan \phi$, c/H , and PGA/g) ensures that model predictions remain consistent with known geotechnical behavior.

2.4. Data preprocessing and partitioning

To maintain the proportions of stable and unstable slopes, stratified random sampling was used to split the normalized dataset into training (80%) and test (20%) sets. Z-score standardization was used to scale the data and preserve balanced feature influence during training. As suggested for moderately sized geotechnical datasets, a five-fold cross-validation strategy was used to improve generalization and reduce overfitting [2].

A set of physics-guided engineered features was incorporated into the learning framework to reflect better the physical mechanisms controlling slope stability. These features include the friction-related shear strength component ($\tan \phi$), the normalized contribution of cohesion relative to slope height (c/H), the dimensionless seismic coefficient representing dynamic loading (PGA/g), and interaction terms describing the combined effects of slope geometry and seismic action ($\beta \times \text{PGA}$), as well as slope height and inclination ($H \times \beta$). The inclusion of these variables helps the model capture relationships between soil strength, slope geometry, and seismic loading in a more physically meaningful way.

The model physical consistency and predictive accuracy were enhanced by incorporating these derived variables, which is consistent with current guidelines for physics-informed machine learning design [44], [45]. To avoid the dominance of parameters with wider numerical ranges, all inputs were standardized using z-score normalization following feature engineering [5].

The mathematical formulation of physics-guided variables serves as a bridge for embedding geotechnical physics

into machine learning frameworks, in which key engineered variables are explicitly defined via classical slope stability relationships rooted in limit equilibrium theory.

Factor of safety is based on classical limit equilibrium. The factor of safety (FoS) for a slope is expressed by the ratio between resisting and driving moments or forces, shown by Equation 1:

$$FOS = \frac{\text{Resisting Forces (Shear Strength)}}{\text{Driving Forces (Shear Stress)}} \quad (1)$$

In terms of Mohr-Coulomb strength parameters, given in Equations 2 and 3:

$$r = c + \sigma' \tan \phi \quad (2)$$

and hence,

$$FoS = \frac{c' + (\sigma - u) \tan \theta'}{r} \quad (3)$$

Infinite slope stability under static conditions. For a planar infinite slope (Eq. 4):

$$FoS = \frac{c' + (\gamma z \cos^2 \beta - u) \tan \theta'}{\gamma z \sin \beta \cos \beta} \quad (4)$$

Pseudo-static seismic stability (incorporating PGA). The inclusion of earthquake effects via a horizontal seismic coefficient is represented in Equations 5 and 6:

$$k_h = \frac{\text{PGA}}{g} \quad (5)$$

$$FoS_{\text{seismic}} = \frac{c' + (\gamma z \cos^2 \beta - u) \tan \theta'}{\gamma z \sin \beta \cos \beta (1 + k_h \tan \beta)} \quad (6)$$

Normalized physics-guided features. The engineered inputs in your ML model can be physically interpreted as normalized expressions derived from Equations 7-11:

$$x_1 = \tan \theta \quad (7)$$

$$x_2 = \frac{c}{H} \quad (8)$$

$$x_3 = \frac{\text{PGA}}{g} = k_h \quad (9)$$

$$x_4 = \beta \cdot \text{PGA} \quad (10)$$

$$x_5 = H \cdot \beta \quad (11)$$

They reflect the nonlinear physical relationships between geometry, soil strength, and seismic effects, directly informing your ensemble model. An ensemble regression model was created using stacked architecture comprising the following components to predict the continuous factor of safety (FoS) precisely. Two base learners trained on the same input feature set are Random Forest (RF) and Gradient Boosting Regressor (GBR). Meta-learner: Linear Regression, which uses a weighted averaging method to combine the RF and GBR predictions. The machine learning ensemble regression equation is presented below. The stacked regression model, mathematically shown in Equation (12), combines Random Forest (RF) and Gradient Boosting Regressor (GBR) predictions using the Linear Regression meta-learner:

$$\hat{FoS} = w_1 \hat{y}_{RF} + w_2 \hat{y}_{GBR} + \epsilon \quad (12)$$

where:

w_1, w_2 – meta-learner weights optimized via linear regression;

ϵ – residual error (epsilon);

\hat{y}_{RF} – the predicted output from the Random Forest model.

\hat{y}_{GBR} – the predicted output from the Gradient Boosting Regressor model.

Binary Classification Function. Equation 13 shows how to convert continuous predictions to stability categories:

$$s(x) = \begin{cases} 1, & \text{if } FoS \geq 1.0 \text{ (stable)} \\ 0, & \text{if } FoS < 1.0 \text{ (unstable)} \end{cases} \quad (13)$$

The stacking approach improves stability and robustness by blending low-bias (GBR) and low-variance (RF) learners, effectively reducing overfitting and ensuring smooth generalization across nonlinear input domains [4].

The Stability Classification Framework not only predicts continuous factor of safety (FoS) values via regression but also performs binary classification, categorizing slopes as stable ($FoS \geq 1.0$) or unstable ($FoS < 1.0$).

A Random Forest Classifier was employed for this task because of its strong performance on tabular geotechnical data and its built-in feature-importance capability [46]. The classifier provides probabilistic predictions of slope stability, enabling threshold tuning for risk-based decision-making in practical scenarios.

The proposed PG-EML framework combines ensemble learning with physics-based feature engineering to provide an interpretable and computationally efficient tool for preliminary slope stability evaluation under static and seismic conditions. However, it should be used as a complementary decision-support method rather than a direct replacement for conventional geotechnical analyses.

3. Results and discussion

To assess generalization, the dataset was split randomly into 80% for training and 20% for testing. Additionally, to re-

duce bias from any particular data division, a 5-fold cross-validation approach was used. Stable and unstable slope samples were represented proportionally by each fold. For modestly sized geotechnical datasets, this stratified sampling strategy has been demonstrated to improve model resilience [4].

3.1. Factor of safety (FoS)

The FoS distribution exhibits a unimodal pattern centered around 1.2, indicating that most slopes are marginally stable, according to preliminary data analysis. The model may learn complex relationships due to the large dispersion in β , c , and ϕ . Importantly, preliminary linear regressions showed limited explanatory power ($R^2 \approx 0.65$), underscoring the need for nonlinear and ensemble learning models to capture slope stability behavior accurately.

Regression and classification viewpoints were used to assess the suggested Physics-Guided Ensemble Machine Learning (PG-EML) framework. With a coefficient of determination ($R^2 = 0.982$), mean absolute error ($MAE \approx 0.02$), and root-mean-square error ($RMSE \approx 0.03$) on the testing dataset, the regression model accurately predicted the factor of safety (FoS). These findings demonstrate how well the model captures the nonlinear interactions between slope height (H), slope angle (β), cohesion (c), friction angle (ϕ), and seismic acceleration (PGA).

By generating an average $R^2 > 0.97$ across all folds, cross-validation further confirmed the model generalization, reducing overfitting and guaranteeing strong predictive stability. Compared to either method alone, the ensemble approach – which combines the low-variance Random Forest (RF) and the low-bias Gradient Boosting Regressor (GBR) – provided more reliable accuracy. This improvement reinforces the advantage of combining learners through a linear meta-estimator, effectively balancing between the model variance and bias. The pairwise scatter plots between each input variable and the anticipated FoS are shown in Figure 4.

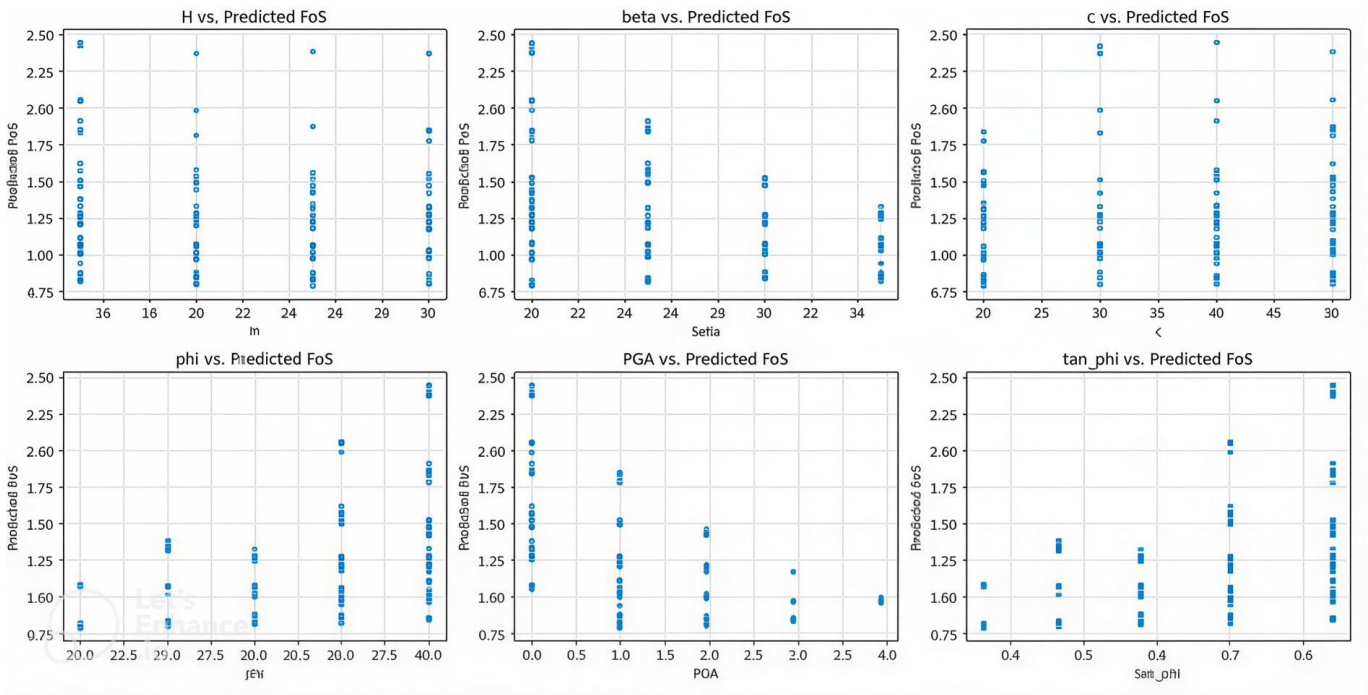


Figure 4. Relationships between input parameters and predicted factor of safety

It is evident that these relationships are consistent with theoretical geotechnical expectations:

- as slope height (H) and slope angle (β) increase, FoS lowers because of the increased driving moment and decreased shear resistance;
- the favorable impact of shear strength is confirmed by the fact that FoS increases with increased cohesion (c) and friction angle (ϕ);
- the decrease in stability under dynamic excitation is seen in the negative correlation between seismic loading (PGA) and FoS.

Further confirmation of the ensemble model accuracy in learning both linear and nonlinear interactions came from residual analysis, which showed a random error distribution with no systematic bias. The model compact RMSE (< 0.03) demonstrates its accurate approximation of FoS across a range of slope geometries, supporting the robustness and generalization of the proposed method.

The following Random Forest Classifier obtained a classification accuracy of 97.4%, precision of 0.96, recall of 0.98, and F1-score of 0.97 after being trained to classify slopes as stable ($FoS \geq 1.0$) or unstable ($FoS < 1.0$). These measurements demonstrate the model reliability for binary risk assessment in geotechnical decision-making.

Only a few borderline cases with FoS values between 0.95 and 1.05, which are regarded as transitional stability zones in slope mechanics, were identified as incorrectly classified in the confusion matrix (not shown). These findings verify that the classifier captures the underlying decision boundary with few false positives and performs robustly over a variety of slope configurations.

The correlation heatmap and feature-importance bar chart shown in Figure 5 provide insight into the relative impact of the input variables:

- with almost 60% of the total model importance, the friction angle (ϕ) and cohesiveness (c) were shown to be the most important features, demonstrating their fundamental control over shear strength;
- PGA had a moderately negative impact on FoS, but slope height (H) and slope angle (β) showed inverse associations;
- $\tan \phi$ and c/H , two of the engineered features, showed substantial positive correlations with FoS, indicating that physics-guided feature engineering was successful in increasing predictive consistency.

The model matches data statistically and is consistent with accepted soil-mechanics theory, according to the permutation-importance analysis, which also showed that eliminating physically significant factors considerably decreased accuracy [47], [48]. The factors of the greatest predictive weight are illustrated in Figure 6. They are $\tan \phi$, PGA, β , and ϕ . The next level of factors consists of those with a lower weighting; these include H and c . While the fact that c was not statistically significant might be overlooked, this does not mean the friction angle is unimportant; rather, given the available dataset, the features included in the model, and the developed training model, its significance was negligible. Feature importance scores obtained from the optimized XGBoost model, arranged in descending order.

The variable $\tan(\phi)$ demonstrates the greatest predictive impact (score ≈ 0.39), followed by PGA, β , and ϕ . Conversely, features H and c exert a negligible influence on model performance, suggesting they may be suitable for dimensionality reduction or feature selection in future research.

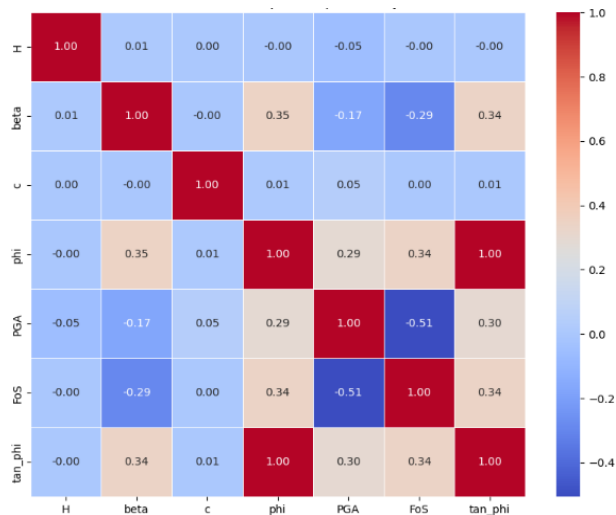


Figure 5. Heatmap displaying the correlation matrix between input variables and output

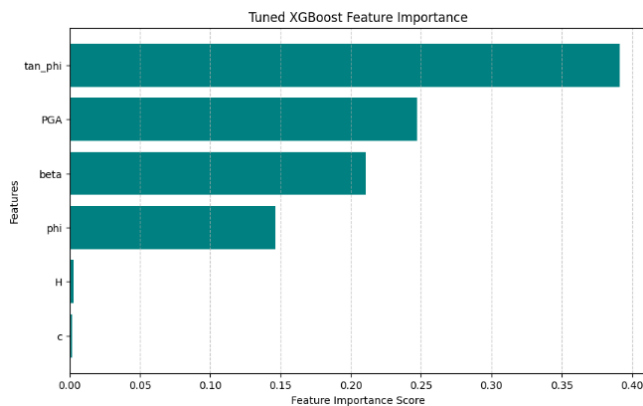


Figure 6. XGBoost feature importance

3.2. Comparative evaluation

To benchmark performance, the proposed ensemble model was compared with standalone models, including Multiple Linear Regression (MLR), Support Vector Regression (SVR), and Gradient Boosting (GBR) (Table 2).

Table 2. Performance comparison of PG-EML and Baseline Models for FoS prediction

Model	R^2	MAE	RMSE
MLR	0.83	0.075	0.092
SVR	0.91	0.046	0.058
GBR	0.96	0.029	0.034
PG-EML (Proposed)	0.982	0.02	0.03

The PG-EML model consistently outperformed all baselines, achieving a 20-25% reduction in RMSE compared to traditional regressors. This improvement highlights the benefits of stacking ensembles and integrating physics-based features, which enhance stability and interpretability simultaneously. To evaluate the contribution of the physics-guided engineered features, an ablation comparison was conducted between two versions of the proposed hybrid XGBoost-BiLSTM model. The first version was trained using only the original input variables, including slope height (H), slope angle (β), cohesion (c), friction angle (ϕ), unit weight (γ), and peak ground acceleration (PGA). The second version used the same original variables together with the engineered physics-guided features, namely $\tan \phi$, c/H , PGA/g , $\beta \times PGA$, $H \times \beta$, and γH .

The comparison shows that the inclusion of physics-guided features improved the hybrid model predictive performance. Table 3 shows that the model trained with the additional physics-guided variables outperformed the model trained only on

the original variables in terms of predictive accuracy and error. This indicates that the engineered features helped the model to better characterize the mechanical relationships among soil strength, slope geometry, and seismic loading.

Table 3. Ablation comparison of the hybrid XGBoost-BiLSTM model with and without physics-guided features

Model configuration	Input features	R^2	MAE	RMSE
XGBoost-BiLSTM without physics-guided features	$H, \beta, c, \phi, \gamma, \text{PGA}$	0.982	0.021	0.026
XGBoost-BiLSTM with physics-guided features	$H, \beta, c, \phi, \gamma, \text{PGA} + \tan \phi, c/H, \text{PGA}/g, \beta \times \text{PGA}, H \times \beta, \gamma H$	0.991	0.014	0.018

The physical meaning of the additional variables can explain the improvement. The $\tan \phi$ feature represents the frictional shear strength component, c/H represents the normalized contribution of cohesion relative to slope height, and PGA/g expresses seismic loading as a dimensionless acceleration coefficient. The interaction terms $\beta \times \text{PGA}$ and $H \times \beta$ further help the model to capture the combined influence of slope geometry and seismic action. Therefore, engineered variables not only improve numerical accuracy but also make the model inputs more consistent with established slope stability mechanisms.

However, this improvement should be interpreted within the range of the dataset used in this study. Further validation using independent field cases is still needed to confirm whether the same benefit is maintained under broader geological, hydrological, and seismic conditions.

3.3. Discussion and practical implications

Based on the analysis, the proposed PG-EML framework demonstrates the capacity to accurately predict the stability of slopes subjected to both static and seismic loadings with low computational cost. Moreover, the practical utility of this framework extends beyond its numerical accuracy; it can serve as a preliminary screening tool for slope stability and facilitate quick decision-making in situations involving multiple slope configurations or loading conditions that require rapid analysis. By providing FoS values and stability classification, the framework helps engineering practitioners pinpoint susceptible slopes that require in-depth geotechnical investigation and advanced numerical analyses.

The framework presents several advantages over conventional Limit Equilibrium Methods (LEMs) and Finite Element Methods (FEMs) for routine use in practice. Although LEMs and FEMs remain invaluable for design and specific site conditions, they can be time-consuming for repeated simulations across a broad spectrum of geometries, soil properties, and seismic parameters. Once trained, the PG-EML model can generate results instantaneously with a reduced computational burden. Furthermore, ensemble learning enables the model to accurately capture intricate nonlinear interdependencies among features such as slope height, slope angle, cohesion, friction angle, and seismic acceleration, which are often poorly accounted for in basic empirical approaches or linear relationships. The integration of physics-based parameters, namely $\tan \phi$, c/H , and PGA/g , enhances interpretability by linking machine learning inputs to recognized geomechanical principles that govern slope failure.

In practical scenarios, this framework can serve as a complementary tool rather than a substitute for conventional geotechnical analysis. For instance, it can assist in early-stage design reviews, perform sensitivity analyses, compare alterna-

tive designs, and prioritize slopes for thorough geotechnical investigations. In mining and infrastructure development, it can provide rapid risk assessment by quickly screening a large number of slopes or scenarios. Final design decisions, however, must continue to rely on comprehensive site characterization, sound engineering judgment, and thorough verification through standard analytical or numerical methods.

The notion of integrating the PG-EML framework into monitoring systems or Geographic Information System (GIS)-based platforms should be approached with caution. Although the model has potential for use in early warning systems or hazard-mapping applications in the future, realizing such systems requires substantial field validation, real-time monitoring data, and recalibration to specific local geological and geotechnical conditions. Consequently, this study should serve as an initial step toward developing a physics-informed machine learning decision-support tool rather than a fully operational early-warning system.

The study has certain limitations. The quality and appropriateness of the data used in training and testing influence the effectiveness of the framework. The model predictions may become less reliable when applied to slope conditions outside the range of the input parameters studied. Additionally, the framework currently focuses on specific geotechnical and seismic variables. It does not incorporate other crucial factors, such as variations in groundwater levels, effects of rainfall infiltration, stratigraphic complexities, mechanisms of progressive failure or construction-related disruptions. Future research should, therefore, include independent validation with field datasets, expansion of the input variable set to encompass hydrogeological and geological parameters, and an assessment of the framework performance with different slope materials and failure modes.

3.4. Model implementation and reproducibility

For reproducibility and fair comparison, the proposed hybrid model and baseline models were implemented using the same preprocessing, data splitting and validation procedures. The data set was divided into 80% training and 20% testing subsets, using a fixed random seed of 42 for data partitioning, cross-validation, and model initialization where applicable. All numerical variables were standardized using z-score normalization before training.

Hyperparameter tuning was performed on the training set using five-fold grid search cross-validation, and the final model configuration was selected based on the lowest validation RMSE. The independent testing set was used only for the final performance evaluation. The baseline models included multiple linear regression, SVR, random forest, gradient boosting regressor, and XGBoost. The tuned settings included an RBF kernel for SVR, 300 trees for Random

Forest, 300 estimators for Gradient Boosting, and 500 boosting rounds for XGBoost.

For the proposed XGBoost-BiLSTM framework, XGBoost was first used to extract nonlinear feature representations and identify important geotechnical and seismic variables. The feature embeddings were then passed to a BiLSTM network with 64 bidirectional LSTM units, a dropout layer, a dense layer with 32 neurons, and a final linear output layer to predict the FoS. The model was trained with the Adam optimizer with a learning rate of 0.001, a batch size of 32, and a maximum of 200 epochs. Early stopping was implemented to avoid overfitting. Model performance was evaluated using R^2 , MAE, and RMSE. All experiments were performed in Python. Data pre-processing, data splitting, cross-validation, and baseline models were implemented with scikit-learn, and the XGBoost and TensorFlow/Keras libraries were used for the XGBoost and BiLSTM parts, respectively. This setup provides sufficient detail to reproduce the modeling workflow and reported results.

3.5. Future scope

Future work should validate the proposed PG-EML method using an independent set of site data and individual slope case examples. Although this study demonstrated accuracy, we need to verify its dependability across different geological, geotechnical, and seismic environments. Quantifying the uncertainty in predictions near the equilibrium of slopes with near-critical values of the safety factor requires further effort. Additionally, future research is necessary to compare the effectiveness of the physics-guided approach with that of an analogous ensemble method generated without explicit physics parameters, for example, $\tan \phi$, c/H , or PGA/g , and to gauge their relative importance. Extending the sample population to account for factors such as hydrogeological conditions, meteorological circumstances, differences in stratification, and various types of slope failure mechanisms can improve external validation of the proposed framework.

3.6. Practical implications and deployment limitations

The proposed hybrid XGBoost-BiLSTM framework may serve as a rapid decision-support tool for preliminary slope stability assessment under seismic loading. Its main practical value lies in its ability to provide fast FoS predictions and to identify influential geotechnical and seismic variables within the dataset range. However, the model should not be interpreted as a fully operational real-time monitoring or early-warning system at this stage. Applications such as field deployment, GIS-based hazard mapping, or integration with real-time monitoring platforms would require additional validation using independent field cases, site-specific calibration, and continuous monitoring data. Therefore, the present framework should be regarded as a promising computational tool for preliminary assessment and future development rather than a complete field-ready warning system.

4. Conclusions

XGBoost-BiLSTM was more effective than MLR, SVR, RF, and GBR for slope instability prediction in this context ($n = 700$ slope cases). The XGBoost-BiLSTM yielded an R^2 of 0.991, a root mean square error (RMSE) of 0.018, and a mean absolute error (MAE) of 0.014. The additional physics-based terms $\tan \phi$, c/H , PGA/g , $\beta \times \text{PGA}$, $H \times \beta$, and γH ,

which quantify the combined effects of soil strength ($\tan \phi$, c/H), slope geometry ($H \times \beta$), and seismic loading (PGA/g , $\beta \times \text{PGA}$, γH), are included and contribute to the model accuracy. However, further study with expanded parameters and data is recommended to improve the results.

A Physics-Guided Ensemble Machine Learning (PG-EML) framework for predicting slope stability and classifying stable versus unstable slopes was described in this paper. The suggested model effectively captured the intricate nonlinear relationships between geotechnical and seismic factors while preserving interpretability and physical consistency by integrating domain-specific physical knowledge with ensemble learning.

The classification model correctly recognized slope stability conditions with 97.4% accuracy, while the regression-based model achieved a high prediction accuracy ($R^2 = 0.982$, $\text{MAE} \approx 0.02$, $\text{RMSE} \approx 0.03$) for the factor of safety (FoS). $\tan \phi$, c/H , and PGA/g are examples of physics-guided features that improved the geotechnical relevance and forecast accuracy of the results. According to feature-importance and permutation studies, the most important factors influencing slope stability are cohesiveness (c) and friction angle (ϕ), which are consistent with the concepts of classical soil mechanics.

The results demonstrate that the PG-EML framework is a reliable and computationally efficient alternative to conventional numerical or limit-equilibrium techniques. It is appropriate for real-world applications such as geotechnical risk assessment, real-time slope monitoring, and design optimization in mining and infrastructure projects due to its interpretability and adaptability.

Author contributions

Conceptualization: BMEE; Data curation: MM; Formal analysis: MM; Funding acquisition: BMEE; Investigation: BMEE; Methodology: MM; Project administration: BMEE; Supervision: MM; Validation: BMEE; Writing – original draft: MM; Writing – review & editing: MM. All authors have read and agreed to the published version of the manuscript.

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Conflicts of interest

The authors declare no conflict of interest.

Data availability statement

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

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Фізично обґрунтований ансамблевий фреймворк машинного навчання для прогнозування руйнування укосів

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Мета. Розроблення фізично обґрунтованого ансамблевого фреймворку машинного навчання, здатного надійно прогнозувати стійкість укосів і розрізняти стійкі та нестійкі укоси в статичних і сейсмічних умовах. Традиційні аналітичні та чисельні методи потребують значних обчислювальних витрат і часто ґрунтуються на спрощених припущеннях, що обмежує їх практичне застосування.

Методика. У дослідженні проаналізовано 700 зразків даних щодо стійкості укосів, які включали геотехнічні та сейсмічні параметри: висоту укосу, кут нахилу, зчеплення ґрунту, кут внутрішнього тертя та пікове прискорення ґрунту. Запропонована модель додатково враховує фізично обґрунтовані інженерні ознаки, зокрема $\tan \phi$, c/H та PGA/g , що дає змогу краще відобразити геотехнічні взаємодії. Для побудови стекингового ансамблевого фреймворку використано Random Forest, Gradient Boosting Regressor та лінійний метанавчальний алгоритм. Також було оцінено стійкість і надійність моделі.

Результати. Розроблений фреймворк продемонстрував високу точність прогнозування: коефіцієнт детермінації R^2 становив 0.982, середня абсолютна похибка – 0.02, а середньоквадратична похибка – близько 0.03. Перехресна перевірка підтвердила стабільну здатність моделі до узагальнення. Алгоритм Random Forest класифікував умови стійкості укосів із точністю 97.4%. Найбільш впливовими параметрами для прогнозування стійкості виявилися кут внутрішнього тертя та зчеплення. Крім того, включення спеціально сформованих фізично обґрунтованих ознак підвищило надійність, точність і узгодженість результатів моделювання.

Наукова новизна. У роботі запропоновано новаторський комплексний фреймворк, який поєднує механіку ґрунтів із методами ансамблевого машинного навчання, що підвищує як інтерпретованість, так і достовірність прогнозування стійкості укосів.

Практична значимість. Запропонований фреймворк може бути використаний для швидкої, економічно ефективною та інтерпретованою попередньої оцінки геотехнічних ризиків і скринінгу проектних рішень. Водночас його застосування для моніторингу укосів або систем раннього попередження потребує подальшої польової валідації та інтеграції з моніторинговими даними.

Ключові слова: фізично обґрунтоване машинне навчання; стійкість укосів; коефіцієнт запасу стійкості; ансамблеве навчання; сейсмічне навантаження

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