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A decision-support framework for slope stability analysis: Prediction and Reinforcement Optimization Using Machine Learning

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Abstract

Slope stability analysis is an important task in geotechnical engineering but predicting the Factor of Safety (FS) and the optimal remediation strategy for unstable slopes is a complex and resource-consuming challenge. This study introduces a novel, two-stage artificial intelligence (AI) framework to be used as a complete decision support tool for engineers. First, comparative analysis of multiple machine learning (ML) models, which includes Linear Regression, Random Forest, XGBoost and LightGBM, was performed on a large synthetic data of 10,000 slope simulations. The LightGBM model for the prediction of the Factor of Safety showed good results in its prediction accuracy. Second, this optimized prediction model was incorporated in a "Smart Optimizer" tool. If a predicted slope is determined to be unstable ($FS < 1.0$), this tool automatically simulates the geotechnical effects of four common reinforcement techniques including: Retaining Walls, Soil Nailing, Geosynthetics, and Drainage. By comparing the predicted FS for all the different scenarios, the tool gives a clear indication of which stabilization method is the best. This framework goes beyond simply predicting stability to provide actionable and data-driven optimization to deliver a fast and reliable system for improving the safety and design efficiency of geotechnical projects.

Keywords: Slope Stability; Machine Learning; LightGBM; Factor of Safety; Optimization; Decision Support; Geotechnical Engineering.

1. Introduction

One of the most critical aspects of geotechnical engineering is slope stability, which has direct effects on infrastructure works security, transport system routes and cities and towns development. The slope failures including landslides and mudslides are serious geohazards that may lead to significant economic damages and serious dangers to human life. The slope stability analysis has traditionally been conducted on the deterministic approaches to the slope stability, including Limit Equilibrium Method (LEM) and Finite Element Method (FEM). Although these techniques have been well tested, they are usually computationally intensive, time consuming and inadequate in their capabilities to represent with great efficacy the natural uncertainty and spatial variability of soil characteristics. Between the past few decades, the research on machine learning (ML) and artificial intelligence (AI) application in slope stability analysis is quite numerous [1-15]. These scientific methods have been highly promising in simulating the non-linear and intricate behaviour of geotechnical systems to give quick and accurate forecasts of slope safety. Many of the various ML models, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forests (RF) and Gaussian Process Regression (GPR) have been effective in predicting the Factor of Safety (FOS) or slope classification (stable or unstable) [1,2,7,8]. Optimization algorithms have further been used to improve the performance of the models through feature selection or hyperparameter tuning [1,8,11].

Despite these advances, a large number of existing studies only focus on prediction. The most important engineering problem in slope stability problems is not the determination of an unstable slope, but rather the design of effective,

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economical, and safe reinforcement schemes. However, the combination of ML-based prediction and reinforcement design optimization has not been widely discussed in the existing literature.

In this study a novel - two-stage - Artificial Intelligence framework is presented to counteract this gap between prediction and practical optimization. The framework consists of:

- **A high-performance FS Prediction Model:** The model was developed by training and comparing multiple ML algorithms on a sturdy dataset of 10,000 examples of the slope and a LightGBM model was chosen due to its accuracy.
- **A "Smart Optimizer" Decision-Support Tool:** This is a tool that uses the trained model not only to check the stability of a natural, un-reinforced slope. If the slope is judged to be unstable, the tool then moves on to simulate the impact of four different engineering interventions (Retaining Walls, Soil Nailing, Geosynthetics, and Drainage) and recommends the solution which results in the highest resulting Factor of Safety.

The contribution of this work consists of a practical and end-to-end system that goes beyond passive prediction and focuses on active design recommendation, which will give engineers a powerful tool to speed up and enhance the reliability of geometric slope stability analysis andould remediation design.

2. Literature Review

The use of machine learning in geotechnical engineering has been rapidly developing with the focus on improving the accuracy and efficiency of slope stability analysis. The literature can be thematically grouped in the scientific articles related to model comparisons for stability prediction, the use of optimization for model enhancement and emerging trends towards decision-support and interpretability.

2.1. Machine Learning for Slope Stability Prediction

A significant portion of the research has been dedicated to comparing the performance of various ML algorithms for predicting the Factor of Safety (FOS) or classifying slope stability. A consensus has emerged that ML models frequently outperform traditional analytical methods and simpler statistical approaches like multiple linear regression [3, 4].

Artificial Neural Networks (ANN) and Multilayer Perceptrons (MLP): These networks are always mentioned as the best ones. Nanehkaran et al. [2] discovered that MLP provided the best accuracy (0.901) and low loss than that of SVM, DT and RF. On the same note, Tien Bui et al. [3] compared five regression methods and observed that MLP had the highest cumulative performance score. Ahangari Nanehkaran et al. [6] also reported that MLP was the most suitable model, having 0.938 precision, to predict FOS in the South Pars region of Iran.

Support Vector Machines (SVM/SVR): SVMs are highly acclaimed to be very strong particularly when optimized. Qi and Tang [1] discovered that an SVM augmented with a hyperparameter optimization firefly algorithm provided the best overall performance of six ML models. Lin et al. [4] also pointed out that SVM and other nonlinear approaches (GBR, Bagging) provide better results.

Ensemble Methods (RF, GBR, XGBoost): Ensemble models are decision trees that have been combined to form a single model, and they are characterized by good accuracy and the capability to operate with complex data. Yang et al. [8] discovered that a Random Forest (RF) model using KS cutoff was the best suited to stability prediction. In their comparison, Waris et al. [9] also considered XGBoost, which demonstrates the effectiveness of the current technologies of gradient boosting.

Gaussian Process Regression (GPR): GPR is singled out because it is incredibly accurate especially when it is applied in research that involves huge synthetic datasets. Among six ML techniques, Mahmoodzadeh et al. [7] discovered that GPR performed best ($R^2 = 0.8139$). Waris et al. [9] obtained close to perfect accuracy of GPR in a study involving more than 19,000 cases ($R^2 = 99.8$ percent on test data) which demonstrates the potential of GPR to produce a reliable surrogate model.

Advanced Deep Learning (DL): Outside of these more basic models, there is research pushing out to more advanced architectures. Zerouali et al. [11] investigated RNNs, LSTMs, and Generative Adversarial Networks (GANs) and came up with a GAN-based model with an accuracy of 95% as well. A more extended survey of Zhang et al. [14] verifies an increased trend in the usage of FNN, RNN, CNN, and GANs in geotechnical engineering.

2.2. Model Enhancement: Optimization and Feature Importance

Researchers have understood that the results of an ML model do not only rely on the algorithm, but also on the merits of its inputs and a second level of optimization.

Hyperparameter Optimization: Some studies have shown considerable performance improvement when using metaheuristic algorithms to optimize the model hyper-parameters. They may be the firefly algorithm [1], genetic algorithms [8], and other new algorithms such as particle swarm optimization (PSO) and a black widow optimization (BWOA) [12].

Feature Importance and Selection: Explaining the most significant parameters in impacting stability is one of the essential findings. The factor of cohesion is consistently discovered to be one of the most significant ones [1, 8, 11]. The internal friction angle [7], unit weight and slope height [11] are other important parameters. By employing a new bGGO feature selection method Zerouali et al. [11] improved the accuracy of their model once again proving the importance of paying attention to most significant inputs.

Interpretability (XAI): One of the biggest problems of ML is the black box problem. Models need to be explainable in order to foster trust and shift towards pragmatic decision-support. Waris et al. [9] took this expressly, through SHAP (SHapley Additive explanations) values, to make their model outputs more interpretable, making the results of their model physically coherent and interpretable.

2.3. Emerging Trends and The Research Gap

Although the literature predicts that the general awareness is still prediction, several studies have suggested that the research is shifting toward more extensive data-driven systems. The algorithmic framework of real-time displacement detection and risk classification that was developed by Alshboul et al. [13] was a genuine decision support system on a construction site that was under active construction. Li et al. [5] have developed a surrogate model that can, in addition to predicting FOS with high accuracy ($R^2 = 0.9989$), classify slopes as either stable, marginally stable and unstable, a finer evaluation. The new trend can be best encapsulated with the point that Phoon and Zhang [15] make that the future of ML in geotechnics will be data-centric, practice-central. They suggest that the field must go beyond the development of algorithms and develop tools that are "indispensable in practice" and use digital technologies to create intelligent, updating tools such as digital twins.

Despite this advancement, there is a major gap. The existing literature, although comprehensive in its handling of prediction, ends up leaving a gap when it comes to the next engineering decision, that of reinforcement design. No integrated framework exists whereby the ML-based prediction of the instability is linked to an ML-based optimization of the solution. This thesis is a direct attempt to address this void, by proposing a framework that incorporates both the prediction and reinforcement optimization in order to provide a truly indispensable decision support system as envisaged by Phoon and Zhang [15].

3. Methodology

The methodology for this study is organized as a two-step process; (1) the creation of a high accuracy predictive model for Factor of Safety (FS) and (2) the integration of the model into a "Smart Optimizer" decision-support framework. An overview of the overall workflow is shown in Figure 1.

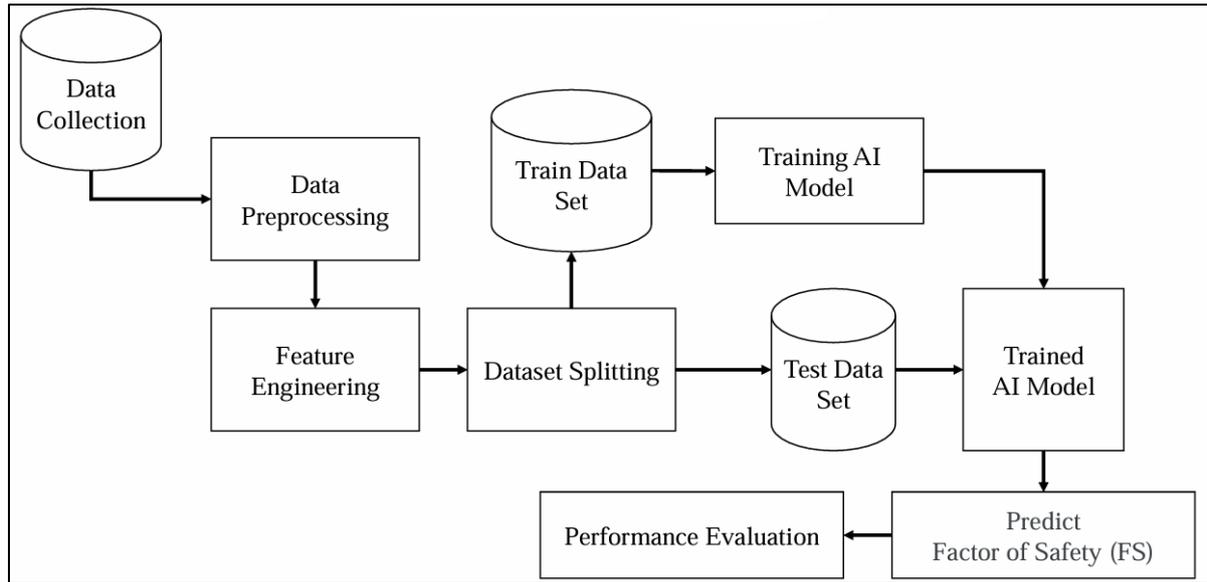


Figure 1 Methodology of This Study.

3.1. Data Acquisition and Description

The data set used for this study is a large, synthetic data set of 10,000 slope stability simulations hosted on Kaggle [16]. This dataset was specially selected as it offers large and diverse set of simulated Geotechnical scenarios which are very important to train robust machine learning models. The dataset contains 10,000 unique values, each of which is characterized by 8 main parameters. These are classified in input features (geotechnical properties) and one target variable (the resulting Factor of Safety).

3.1.1. Input Features (Predictors)

As shown in Table 1, the dataset includes seven input features that define the physical and hydrological properties of the slope and any applied interventions.

3.1.2. Target Variable (Output)

Factor of Safety (FS) is the continuous-valued target variable that the models are trained to predict. It represents the ratio of resisting forces to driving forces, with $FS < 1.0$ indicating instability.

Table 1 Input Features of the Dataset.

Category	Feature	Unit	Description
Geometrical Properties	Slope Angle	°	The angle of the slope incline
	Slope Height	m	The vertical height of the slope.
Soil Mechanical Properties	Unit Weight	kN/m ³	The weight of the soil per unit volume.
	Cohesion	kPa	The 'stickiness' or intrinsic shear strength of the soil
	Friction Angle	°	A measure of the soil's shear strength derived from friction between particles.
Hydrological Conditions	Pore Water Pressure Ratio	ru	Represents the pressure of water within the soil pores, which counteracts soil strength.
Engineering Intervention	Reinforcement Type	text	A categorical feature specifying the stabilization method applied. This includes five scenarios: 'Natural' (no reinforcement), 'Retaining Wall', 'Soil Nailing', 'Geosynthetics', and 'Drainage'

This dataset's structure that relates geotechnical inputs and reinforcement types explicitly to a given FS, is ideally suited for the two stage objective of this study which was first to accurately predict FS and second to systematically assess the effectiveness of different stabilization measures.

3.2. Data Preprocessing and Exploratory Data Analysis (EDA)

Prior to training the machine learning models, the dataset underwent a thorough EDA and preprocessing workflow in order to insure the quality of the data and its compatibility with machine learning algorithms. First, an EDA was performed, to understand what was the underlying structure or the relationships of the data. This involved creating descriptive statistics for all parameters (Table 2), the histograms to provide a visual of the distribution of each feature (Figure 2), and a heatmap of correlations (Figure 3) to detect linear correlations between variables.

Table 2 Dataset Descriptive Statistics.

Params	Unit Weight	Cohesion	Internal Friction Angle	Slope Angle	Slope Height	Pore Water Pressure Ratio	Factor of Safety
mean	19.9415	27.7038	32.5012	34.9356	27.3588	0.5031	2.5450
std	2.8763	13.0182	7.1693	14.4497	13.0177	0.2883	0.6599
min	15.0001	5.0070	20.0012	10.0002	5.0007	0.0000	0.5000
max	24.9971	49.9966	44.9975	59.9894	49.9987	0.9999	3.0000

Table 2 shows the descriptive statistics of geotechnical and slope parameters used for the study. For each parameter, the table gives the summary statistics for the parameter, including mean, standard deviation, min, and max, giving a good sense of the pattern of variability and range that is found within the data. The mean unit weight is about 19.94 kN/m³, and the values range from 15.00 kN/m³ to 24.99 kN/m³, which implies that the unit weight is moderately variable. Cohesion is distributed wider with mean value 27.70 kPa and standard deviation of 13.02 kPa showing various soil condition. The internal friction angle range is from 20.00deg to 44.99deg with a mean value of 32.50deg, indicating a wide variety of shear strength properties. Slope-related parameters are also subject to large variation. Slope angle varies between 10.00 to 59.99 degrees with an average value of 34.94 degrees; and slope height varies between 5.00 to 49.99 meters with an average value of 27.36 meters. The mean value of the pore water pressure ratio is 0.503 with a fluctuating value (from 0 to 0.999) indicating the diversity of groundwater condition of the data set. Finally, the factor of safety varies from 0.50 to 3.00 and the average value is 2.545 which indicates different stability conditions among the slope cases.

Figure 2 shows the distribution patterns of the geotechnical parameters used in the study; the variability and spread of each feature across the dataset can be seen. The histograms along with kernel density estimation (KDE) curves are a visual way of seeing the distribution of each variable in its own range. The distribution of the Unit Weight is quite uniform between ca. 15 and 25 kN/m³ with a slight tendency towards the mid-range values. Cohesion has a wide and evenly spread distribution between 5 and 50 kPa, which shows that there is much variation of the shear resistance in the soil across the samples.

Similarly, the Internal Friction Angle is shown to have a very uniform distribution from 20deg to 45deg representing a diversity of shear strength characteristics. The Slope Angle distribution ranges from 10 degrees to 60 degrees and the distribution seems to be rather distributed, suggesting that a variety of slopes will be included in the dataset. In the case of Slope Height, the values are between 5 m and 50 m, with the distribution again looking fairly equal, meaning that presumably the dataset describes a wide range of slope geometries. Lastly, the Pore Water Pressure Ratio demonstrates an even spread between 0 and 1 which captures different conditions in terms of pore pressure from dry to fully saturated conditions.

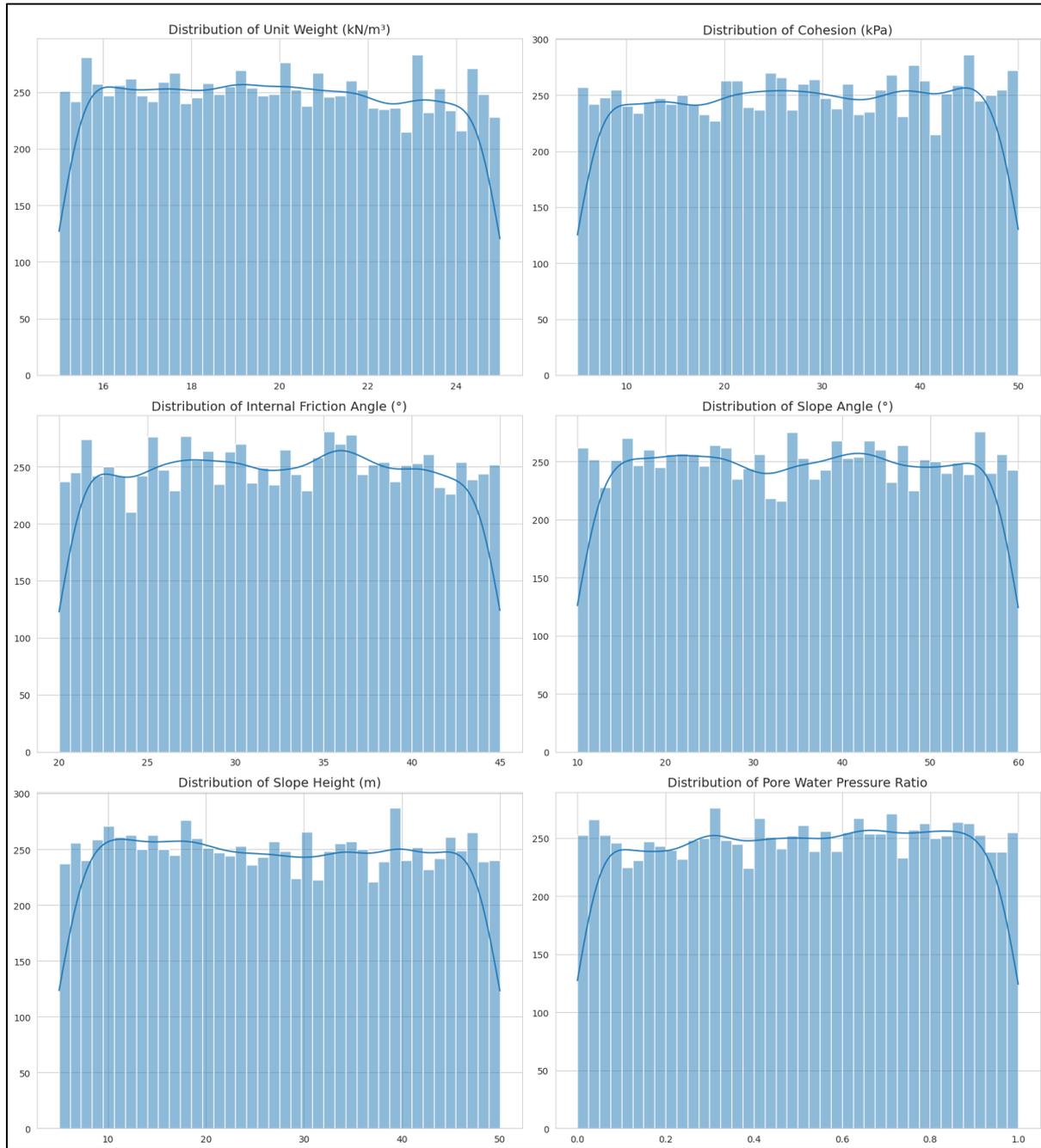


Figure 2 Distribution of Geotechnical Features.

The correlation heatmap of the used geotechnical features is presented in Figure 3. In all, the correlations between most of the input variables are very weak, indicating that the data sets don't suffer from a problem of multicollinearity. The only significant correlation is observed between the Cohesion and Factor of Safety, giving a positive relation, that is, a high cohesion will generally lead to a high safety factor. Moderate correlations are also evident between Internal Friction Angle and the Factor of Safety. All other pairs of parameters have a near-zero correlation, which confirms that the features have independent contribution to the data set and the predictive modelling process.



Figure 3 Correlation Heatmap of Geotechnical Features.

Additionally, the effect of the categorical Reinforcement Type on Factor of Safety (FS) was studied. Box plots were created to compare the distribution of FS values for each of the 5 reinforcement scenarios (Natural, Retaining Wall, Soil Nailing, Geosynthetics, and Drainage) as shown in Figure 4. This analysis gave preliminary information on the effectiveness of each intervention in a general sense, indicating the expected increase of FS for reinforced slopes in comparison to natural slopes.

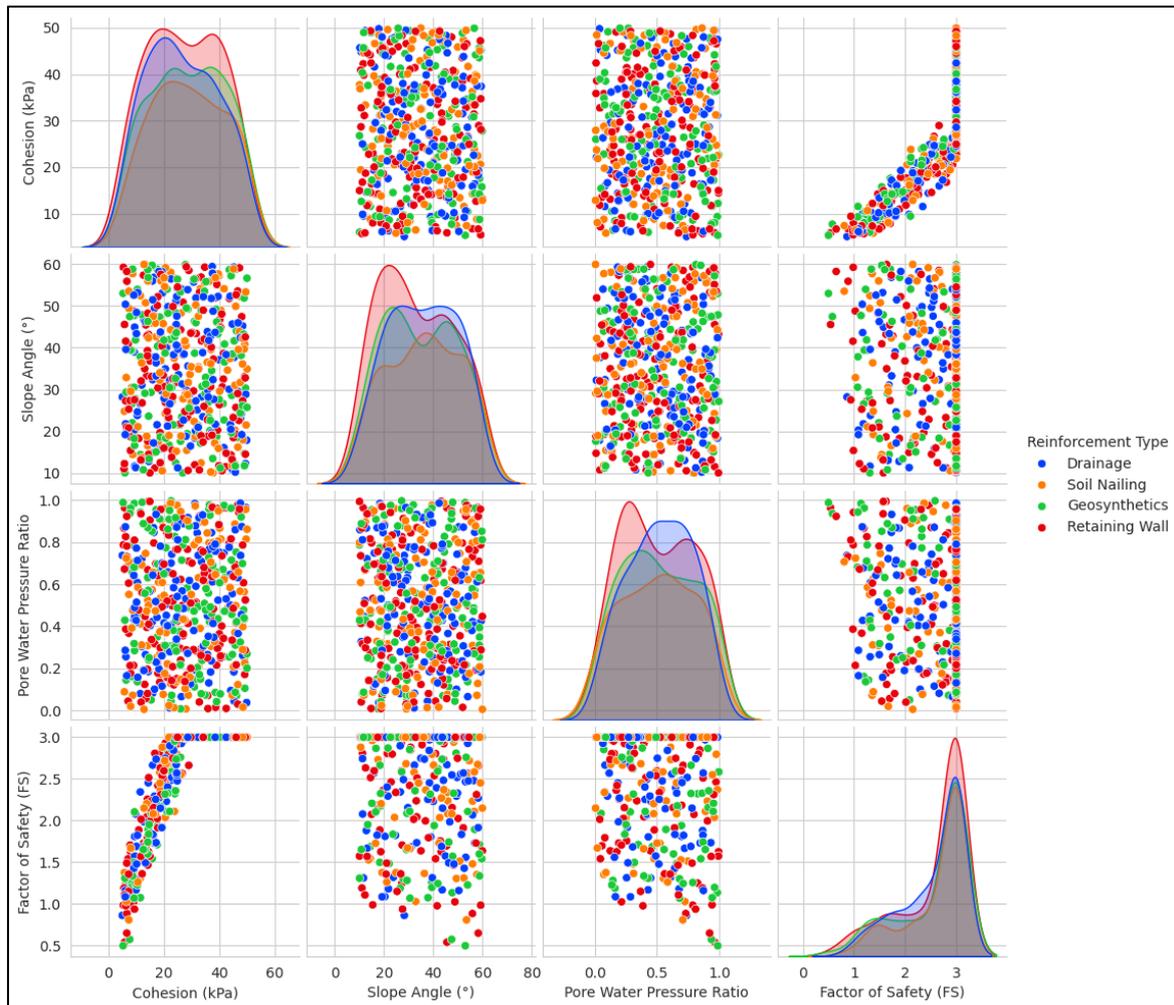


Figure 4 Distribution of Factor of Safety (FS) for each Reinforcement Type.

To preprocess the data, one-hot, the Categorical Reinforcement Type feature was transformed into a numerical form. This step generates distinct binary (0 or 1) columns according to each category of reinforcement such that the models can understand such information. The continuous numerical factors were then made normal with the help of StandardScaler which makes the data to have a mean of zero and a standard deviation of one. This step is important when the models being considered are sensitive to the magnitude of input features like Linear Regression. Lastly, the entire preprocessed dataset was divided into a training and a testing set of 80:20 samples correspondingly. 8,000 samples would be used to train the model, with the rest of the 2,000 samples to be reserved in the end to test the final model.

3.3. Predictive Model Development and Comparison

The main purpose of this phase was to come up with a very precise model in the prediction of the Factor of Safety (FS). Four different regression algorithms were trained and tested that are selected due to different approaches to learning using the data:

- **Linear Regression:** This is a simple model that will determine a linear relationship between the input features and the target FS.
- **Random Forest Regressor:** It is an ensemble technique that creates several decision trees and combines them to obtain more precise and consistent forecasting.
- **XGBoost Regressor:** It is a gradient-boosted decision-tree algorithm that was developed as a high-performing and efficient algorithm.
- **LightGBM Regressor:** A fast-performing gradient-boosting model, as well as analogous to XGBoost, which employs tree-based learning models..

All four models were trained on the 8,000-sample training set, which included the scaled geotechnical features and the one-hot encoded reinforcement types. Their predictive performance was then benchmarked on the unseen 2,000-sample testing set. The models were compared using three standard regression metrics:

- R-squared (R²): The ratio of the variance of the FS that can be predicted through the input features.
- Mean Squared Error (MSE): The mean of the squares of the errors, which is very severely punitive of large prediction errors.
- Mean Absolute Error (MAE): The mean value of the difference between predicted and actual FS.

The comparative analysis results, presented in Section 3, showed that LightGBM model exhibited the best R² and the lowest values of the error metrics and, thus, presents better predictive accuracy. This model was thus chosen to be the best model to be incorporated into the decision-support framework.

3.4. Development of the Two-Stage Decision-Support Framework

The final phase of the methodology involved constructing the two-stage AI tool. This tool integrates the trained ML models into a practical, sequential workflow for engineers.

3.4.1. Stage 1: The Stability Checker

The first component is a rapid stability assessment tool. A *separate* LightGBM model was trained specifically for this task, using *only* the subset of data corresponding to 'Natural' (un-reinforced) slopes.

- Purpose: To provide an immediate prediction of stability for a natural slope before any reinforcement is considered.
- Input: The six geotechnical features of the slope (e.g., Slope Angle, Height, Cohesion, etc.).
- Process: The tool feeds these inputs into the "Natural Slope" LightGBM model.
- Output: The predicted FS value and a simple classification: "STABLE" (FS \geq 1.0) or "UNSTABLE" (FS < 1.0).

3.4.2. Stage 2: The Smart Optimizer

This is the framework's core optimization engine, which is automatically triggered if the Stability Checker identifies a slope as "UNSTABLE".

- Purpose: To systematically test all available reinforcement options and recommend the most effective one.
- Input: The same six geotechnical features of the unstable slope.
- Process: The optimizer utilizes the "best model" trained on the *entire* dataset. It programmatically simulates the application of each of the four reinforcement techniques:

It creates four copies of the slope's input data.

To each copy, it appends the one-hot encoded vector for 'Retaining Wall', 'Soil Nailing', 'Geosynthetics', and 'Drainage', respectively.

It runs all four synthetic scenarios through the predictive model to obtain four distinct FS values.

Output: A ranked list of all four reinforcement options and their predicted FS values, culminating in a clear "Recommendation" for the option that yields the highest Factor of Safety.

4. Performance Evaluation and Model Selection

This section introduces the results of the comparative analysis described in previous section. The four candidate models (i.e. Linear Regression, Random Forest, XGBoost and LightGBM) were fitted on the 8000 samples data set for training and further tested on 2000 samples data set for unseen test. The goal was to identify the model with the highest predictive accuracy to be integrated in the decision support structure.

4.1. Comparative Model Performance

Table 3 summarizes the performance of all the four models on the test set in terms of R-squared, Mean squared error, and Mean Absolute error.

Table 3 Model Performance Summary.

Model	R-squared (R ²)	Mean Squared Error (MSE)	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)
Linear Regression	0.730099	0.115382	0.290383	0.339679
Random Forest	0.995965	0.001725	0.022417	0.041534
XGBoost	0.996839	0.001352	0.021266	0.036763
LightGBM	0.998227	0.000758	0.015687	0.027529

The results clearly show that tree-based ensemble methods (Random Forest, XGBoost and LightGBM) perform much better than the base model of Linear Regression. This implies that there are complex and non-linear relationships between the geotechnical parameters and the Factor of Safety.

Among the ensemble methods, the LightGBM model has the strongest performance with the highest R² value (almost 99.82) and the lowest MSE and MAE. This high degree of accuracy indicates that the model is close to the simulated ground-truth values in determining the predictions.

4.2. Model Selection for Framework Integration

Based on its superior performance metrics (R², MSE, and MAE) and its confirmed ability to capture established geotechnical relationships, the LightGBM model was selected as the "best model" for two key tasks:

As the predictive engine for the Stage 2: Smart Optimizer, where it is used to evaluate the FS for different reinforcement scenarios.

As the base algorithm for the Stage 1: Stability Checker, which was a separate model trained only on the 'Natural' slope data.

5. Discussion

This section provides a demonstration of the practical application of the complete two-stage decision support framework. A case study was performed on a high-risk slope with difficult geotechnical parameters to simulate a real world engineering problem.

5.1. Case Study: Analysis of an Unstable Slope

To test the framework, a hypothetical slope was defined with the following high-risk parameters, taken from the test dataset:

Slope Angle: 31.8°

Slope Height: 49.8 m

Pore Water Pressure Ratio: 0.73

(Other parameters: Cohesion=18.6 kPa, Friction Angle=17.7°, Unit Weight=19.3 kN/m³)

5.2. Stage 1: Stability Checker Result

The slope's parameters for a 'Natural' (un-reinforced) state were first fed into the Stage 1: Stability Checker. This model, trained only on natural slopes, provided an immediate stability assessment.

Predicted FS (Natural): 0.888

Result: UNSTABLE

As the predicted Factor of Safety was well below the 1.0 threshold, the framework correctly identified the slope as unstable and a high risk for failure, automatically proceeding to the next stage.

5.3. Stage 2: Smart Optimizer Recommendation

Having identified the slope as unstable, the framework's Stage 2: Smart Optimizer was triggered. This component used the comprehensive LightGBM model (trained on all data) to systematically simulate the application of all four reinforcement techniques to this specific slope. The results generated by the optimizer are presented in Table 4.

Table 4 Result of Optimizer in Case Study.

Reinforcement Method	Predicted FS	Predicted Stability
Retaining Wall	0.895	UNSTABLE
Soil Nailing	0.893	UNSTABLE
Geosynthetics	0.893	UNSTABLE
Drainage	0.890	UNSTABLE

5.4. Final Recommendation

Based on this analysis, the optimizer identified 'Retaining Wall' as the most effective solution, as it produced the highest predicted Factor of Safety (0.895).

5.5. Discussion of Results

The case study is able to showcase the end-to-end functionality of the framework. It went from a problem (a set of parameters of the slope) to a clear and actionable recommendation. The tool was not only able to identify the problem (FS = 0.888) but also suggest a ranked list of possible solutions that could allow an engineer to make a rapid data-driven decision.

One of the most important points for discussion is obtained from this particular result: even the "best" recommended solution (Retaining Wall, FS = 0.895) was not able to improve the Factor of Safety past this 1.0 level.

This is a vital finding and not a failure of the model. Instead, it accurately maps the patterns of the training data. This result indicates that for this specific combination of severe geotechnical conditions, a regular application of a single reinforcement technique (represented by the "average" scenarios of the database) is not sufficient for guaranteeing stability.

This is an extremely valuable insight to an engineer. The tool has been helpful in demonstrating how a simple, "off-the-shelf" solution is not sufficient. This would direct the engineer to:

- Prioritize the 'Retaining Wall' as the most promising *type* of solution.
- Use their engineering judgment to design a *more robust* retaining wall than the standard-case, or;
- Investigate combination solutions, such as a Retaining Wall combined with Drainage, to achieve the desired target FS (e.g., FS > 1.5).

The framework, therefore, acts as a powerful screening and prioritization tool, rapidly eliminating ineffective options and pointing the engineer toward the most viable path, saving significant time in analysis and design iterations.

6. Conclusion and Future Work

This study has managed to design and test a new two-stage artificial intelligence system that should be applied in full scale as a decision support system by geotechnical engineers. The gap that the work fills is enormous, as the literature currently overlooks the ability of the slope stability to be predicted and then used to optimize action to be taken on the slope to remedy the failure. The first stage of the study was a comparative study of four machine learning models and came up with the conclusion that the LightGBM algorithm could predict the Factor of Safety (FS) with a high R2 and the lowest error values. A feature importance analysis of this model proved that its predictions were based on sound

geotechnical principles and that the most influential parameters are Cohesion and Friction Angle. The second and more important contribution was the implementation and integration of this high-performance model into a 'Smart Optimizer' tool. This tool first evaluates the stability of a natural slope and if it is determined that the slope is unstable ($FS < 1.0$), the tool automatically simulates four common scenarios for reinforcement (Retaining Walls, Soil Nailing, Geosynthetics, and Drainage). By comparing the predicted FS for each intervention it is possible to provide a clear data-driven recommendation for the most efficient stabilization method using the framework.

This end-to-end system presents a practical and faster way for engineers to not only know which slopes are at risk, but to work through the process of efficiently identifying and developing a possible path to mitigate the risk. It is a concrete move towards the "data-centric geotechnics" called for by Phoon & Zhang (2023) where artificial intelligence tools are developed to solve practical and real-world engineering problems.

To build upon this work, future research should focus on the following:

- Real-World Validation: Training and testing the model on a database of real-world slope failure and remediation case studies to validate its practical accuracy.
- Economic Integration: Incorporating a cost-benefit analysis module into the optimizer, allowing it to recommend the most *cost-effective* solution that achieves a target Factor of Safety (e.g., $FS > 1.5$).
- Web-Based Application: Developing the framework into a user-friendly, interactive web application to make it accessible to practicing engineers, students, and researchers, thereby broadening its impact.

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