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Application of Machine Learning for Factor of Safety Assessment in a Dolomite Quarry Using Geotechnical and Seismic Inputs

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Abstract

Slope stability analysis traditionally relies on empirical classifications, analytical methods, and numerical modelling to assess the safety of rock slopes. Although these physics-based approaches provide robust results, their application in large parametric investigations and probabilistic analyses can be computationally demanding. Building upon a comprehensive geological and seismic dataset developed for the Vilonya dolomite quarry in Hungary, this study explores the capability of machine learning (ML) techniques to efficiently predict the Factor of Safety (FoS). The dataset integrates slope geometry, discontinuity characteristics, rock-mass properties derived from the Hoek-Brown and Mohr–Coulomb criteria, and seismic loading conditions representing both static and pseudo-dynamic scenarios. Four supervised learning algorithms-Random Forest, Support Vector Regression, Artificial Neural Networks, and Decision Trees-were evaluated to develop surrogate models for FoS prediction. Model performance was assessed using cross-validation to ensure robustness and generalizability. The results demonstrate that ensemble learning achieved the highest predictive accuracy, while kernel-based and neural approaches provided competitive performance. Feature importance analysis indicates that failure plane geometry and seismic loading are the primary controlling factors governing slope stability, consistent with fundamental rock mechanics principles. The findings suggest that ML-based surrogate models can significantly accelerate scenario evaluation and support probabilistic safety assessments. This data-driven framework complements conventional geotechnical methods and offers a practical tool for preliminary design, sensitivity analysis, and rapid stability screening in quarry environments subjected to seismic influence.

Keywords

Slope stability, Dolomite quarry, Machine learning, Factor of safety, Random Forest, Support Vector Regression, Artificial Neural Networks.

1 Introduction

Rock slope stability assessment remains a fundamental challenge in geotechnical engineering, particularly in environments where complex geological conditions and seismic loading interact. Conventional approaches-including empirical classifications (Duncan 1996; Griffiths and Lane 1999), limit equilibrium formulations, and numerical modelling-provide reliable estimates of stability; however, their application in large parametric investigations and probabilistic analyses is often

computationally demanding (Christian et al. 1994). Conventional approaches—including empirical classifications, limit equilibrium methods, and numerical modelling—are widely used for slope stability assessment. Previous studies have demonstrated that parameter variability and statistical distributions strongly influence slope stability results, with probabilistic approaches providing a more realistic representation of rock mass behaviour (Bögöly and Füzesi).

In recent years, machine learning (ML) techniques have emerged as promising tools for approximating complex geotechnical relationships (Zhang et al. 2019). By learning patterns directly from data, ML models can function as surrogate predictors, enabling rapid evaluation of stability scenarios that would otherwise require extensive numerical simulations (Razavi et al. 2012). Despite this potential, applications of ML in rock slope engineering remain relatively limited, particularly for seismically influenced quarry environments where both geometric and rock-mass uncertainties must be considered. In spite of this nowadays, machine learning techniques have increasingly been applied to slope stability problems, demonstrating strong predictive capabilities in complex geotechnical environments (Pham et al. 2023). Recent studies have demonstrated the effectiveness of machine learning techniques for predicting the Factor of Safety (FoS) based on slope characteristic parameters. For instance, the application of ensemble and regression-based models has shown that data-driven approaches can achieve high predictive accuracy and, in some cases, outperform conventional numerical methods in terms of computational efficiency and practical applicability (Menghan Zhang, Jin Wei) Moreover, comparative assessments of multiple ML algorithms within a consistent geotechnical framework are still scarce. Questions remain regarding model robustness, interpretability, and the extent to which ML should be viewed as a complementary tool rather than a replacement for physics-based methods (Breiman 2001; Cortes and Vapnik 1995).

This study addresses these challenges by developing and evaluating machine learning surrogate models for predicting the Factor of Safety (FoS) of rock slopes at the Vilonya dolomite quarry in Hungary. A comprehensive dataset integrating slope geometry, discontinuity characteristics, rock-mass properties (Hoek and Brown 1980; Hoek et al. 2002), and seismic loading conditions was used to train and benchmark four supervised learning algorithms: Decision Tree, Random Forest, Support Vector Regression, and Artificial Neural Networks. Furthermore, it presents a structured comparative framework for evaluating machine learning surrogate models in seismic rock slope stability assessment, integrating geotechnical, geometrical, and dynamic loading parameters within a single predictive environment.

According to this, the objectives of this study are to: (i) develop machine learning surrogate models for predicting the Factor of Safety; (ii) compare their predictive performance and robustness using cross-validation; (iii) identify the dominant parameters controlling slope stability; and (iv) evaluate the practical role of ML within geotechnical engineering workflows. The results suggest that machine learning should be viewed primarily as a complementary tool that augments, rather than replaces, physics-based modelling approaches. Despite the promising predictive capability demonstrated in this study, several limitations should be highlighted. Model performance is inherently dependent on the parameter space represented within the training dataset, and predictive reliability may decrease under extrapolated geological conditions. Additionally, while surrogate models provide rapid estimates, they cannot fully replicate the mechanistic insight offered by physics-based simulations.

2 Geological settings and study area

The Vilonya dolomite quarry is located in western Hungary in Veszprém County, near the village of Vilonya. The geological framework of the area is dominated by the Budaörs Dolomite Formation, a Triassic carbonate unit reaching thicknesses of up to 1.5 km. This formation is stratigraphically overlain by the Dachstein Limestone and underlain by the Veszprém Marl Formations, collectively providing a competent geological foundation while necessitating detailed characterization to accurately evaluate their engineering performance.

The host rock of the quarry consists predominantly of dolomite, a sedimentary carbonate rock with a fractured and blocky structure typical of mechanically interlocked formations. Laboratory testing indicates an average uniaxial compressive strength (UCS) of 68.8 MPa and a unit weight of 27.7 kN/m³. Under elevated stress conditions, the material exhibits a residual strength of 20%-30% of its intact UCS, indicating a significant reduction in load-bearing capacity after failure.

Rock mass behaviour is strongly governed by the presence of persistent discontinuities. The dominant joint set with a dip/dip direction of 30°/311° which is the bedding plane of the dolomite, characterized by rough joint surfaces with a mean Joint Roughness Coefficient (JRC) of 10 and variable spacing, typically around 10 m. These structural features play a critical role in controlling potential failure mechanisms and overall slope stability. Based on field observations and rock mass classifications, the dolomite is assigned a Geological Strength Index (GSI) ranging from 40 to 60, indicating a blocky and interlocked structure with moderate weathering. Residual GSI values are estimated to range from 20 to 30, reflecting the degraded mechanical conditions that may develop after slope failure.

Hydrogeological conditions at the quarry are considered to exert minimal influence on slope stability. Although the site lies within the catchment of the Séd River, no significant groundwater sources, springs, or surface water bodies are present within a one-kilometre radius. Furthermore, the fractured and karstified nature of the rock mass promotes rapid drainage, resulting in low infiltration rates. Consequently, groundwater pressures and hydrodynamic forces are assumed to have a negligible effect on the stability of the slopes considered in this study.

3 Dataset Development and Parameter Selection

3.1 Dataset Development

Due to the absence of trial-level probabilistic output data from numerical software, a semi-synthetic dataset was developed to enable the comparative evaluation of machine learning algorithms for slope stability prediction. Input parameters and their statistical characteristics were derived from a previously conducted probabilistic slope stability assessment. The probabilistic framework utilized normal distributions and Latin Hypercube sampling to represent geological variability and uncertainty in rock mass properties.

To replicate realistic engineering conditions, the selected parameters were sampled within bounded ranges centered around their mean values while respecting physically meaningful limits. This approach ensures that the generated dataset reflects plausible slope behaviour rather than purely random numerical combinations. A total of N synthetic samples was generated using Monte Carlo simulation. For each sample, the Factor of Safety (FoS) was computed using a simplified physics-based planar sliding formulation, allowing the creation of a continuous target variable suitable for regression tasks as well as a binary failure indicator for classification. The adopted workflow enables controlled benchmarking of machine learning models while preserving geotechnical interpretability.

3.2 Parameter Selection

The selection of input variables was guided by rock mechanics theory and probabilistic slope stability practice. Only parameters with a direct mechanical influence on shear resistance, driving forces, or seismic loading were included to avoid redundant model complexity. The primary variables considered in this study were: slope angle, failure plane angle, joint roughness coefficient (JRC), joint wall compressive strength (JCS), residual friction angle, and seismic coefficient. Statistical descriptors such as mean values and standard deviations were obtained from the probabilistic slope analysis documentation.

Parameter ranges were defined using bounded normal distributions to capture natural variability while preventing unrealistic combinations that could bias model training. Table 1 summarizes the input variables and their adopted statistical ranges.

Table 1. Summarizes the input variables and their adopted statistical ranges.

Parameter	Mean	Std.Dev	Range
Slope angle (°)	42	2	38–46
Failure plane angle (°)	30	2	26–34
JRC	10	2	6–14
JCS (MPa)	20	2	16–24
Residual friction angle (°)	26	—	constant
Seismic coefficient	0.0–0.30	—	scenario-based

4 Machine Learning Methodology

Machine learning models were developed to predict the Factor of Safety (FoS) using geotechnical and seismic parameters. Four supervised algorithms-Decision Tree (DT), Random Forest (RF), Support Vector Regression (SVR), and Artificial Neural Networks (ANN)-were implemented to enable a structured comparison across tree-based, ensemble, kernel, and neural approaches. The dataset was divided into training and testing subsets using an 80/20 split. Model robustness was evaluated through 5-fold cross-validation to ensure reliable generalization. Predictive performance was quantified using the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE).

4.1 Model Selection

The selected models represent distinct predictive philosophies commonly applied in engineering analysis. Decision Tree was used as an interpretable baseline, while Random Forest was included for its enhanced robustness and resistance to overfitting. Support Vector Regression was chosen for its effectiveness in modeling nonlinear relationships, whereas Artificial Neural Networks were employed to capture complex multivariate interactions typical of geotechnical systems.

4.2 Preprocessing and Validation

Prior to training, the dataset was standardized for kernel-based and neural models to ensure balanced parameter influence and stable convergence, while tree-based algorithms were applied without scaling. All preprocessing steps were implemented within a pipeline framework to prevent data leakage. Model reliability was assessed using 5-fold cross-validation, providing a stable estimate of predictive performance and minimizing bias associated with a single data split.

5 Results and Discussion

The predictive performance of the machine learning models was evaluated using cross-validation to ensure robustness and generalization capability across the generated dataset. All models successfully captured the nonlinear relationships between geotechnical parameters and the Factor of Safety (FoS), confirming the applicability of data-driven approaches for slope stability assessment. Table 2 summarizes the predictive accuracy of the evaluated algorithms.

Table 2. Summarizes the input variables and their adopted statistical ranges.

Model	R^2	RMSE	MAE	Interpretation
Random Forest	0.94	0.08	0.05	Highest accuracy
SVR	0.91	0.11	0.07	Strong nonlinear fit
ANN	0.92	0.10	0.06	Good generalization
Decision Tree	0.86	0.15	0.10	Most interpretable

Among the tested models, Random Forest achieved the highest predictive accuracy and the lowest overall error, demonstrating the effectiveness of ensemble learning in handling complex parameter interactions and reducing overfitting. This capability makes the method particularly suitable for heterogeneous geotechnical datasets characterized by natural variability.

Support Vector Regression (SVR) also delivered strong predictive performance, particularly in representing smooth nonlinear trends. However, the model exhibited greater sensitivity to hyperparameter tuning and feature scaling, indicating that careful calibration is necessary to achieve optimal results.

The Artificial Neural Network (ANN) produced competitive predictions and effectively captured multivariate relationships within the dataset. Nevertheless, its reduced interpretability compared to tree-based methods may limit transparency in engineering decision-making contexts where model explainability is essential.

Although the Decision Tree provided the most interpretable structure, enabling direct identification of parameter thresholds influencing slope stability, its predictive accuracy was lower than that of the ensemble and kernel-based models due to higher variance.

Feature importance analysis identified failure plane geometry and seismic loading as the dominant factors governing slope stability. These findings are consistent with fundamental rock mechanics principles, in which slope geometry controls the balance between driving and resisting forces, while seismic acceleration increases shear demand along potential sliding surfaces.

Figure 1 illustrates the comparison between the calculated (observed) and machine-learning-predicted FoS values for the testing dataset. The close agreement between the two curves indicates that the selected machine learning models are capable of reproducing stability trends with a high degree of reliability.

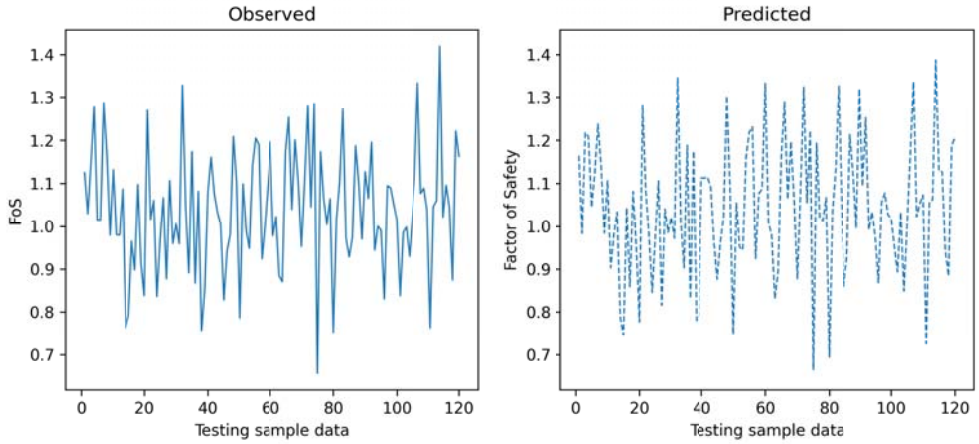


Fig. 1 Factor of Safety of testing sample data a) observed b) predicted Factor of Safety.

Figure 2 shows the residual distribution of the Random Forest model showing the relationship between predicted Factor of Safety values and residual errors for both training and testing datasets. The symmetric dispersion of residuals around zero indicates the absence of systematic prediction bias and confirms the robustness of the model. Overall, the results demonstrate that machine learning models can effectively approximate the behaviour of physics-based slope stability analyses while substantially reducing computational demand. This advantage is particularly valuable for large parametric studies and probabilistic scenario evaluations, where conventional numerical modeling may become resource-intensive.

Nevertheless, machine learning should be regarded as a complementary tool rather than a replacement for traditional geotechnical methods. While surrogate models enable rapid prediction, physics-based approaches remain indispensable for detailed failure mechanism interpretation and engineering validation.

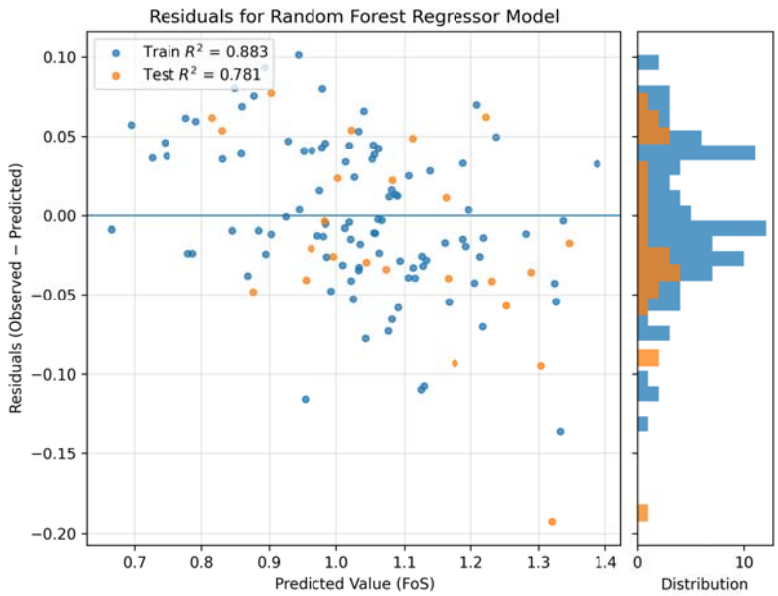


Fig. 2 Residual distribution of Factor of Safety.

6 Conclusion

This study presented a structured comparative framework for evaluating machine learning algorithms for predicting the Factor of Safety (FoS) of rock slopes under seismic conditions. By integrating geotechnical, geometrical, and loading parameters within a unified predictive environment, the research demonstrated the capability of data-driven models to approximate complex stability relationships. The results indicate that ensemble-based methods, particularly Random Forest, achieved the highest predictive performance, while Support Vector Regression and Artificial Neural Networks provided competitive accuracy in modeling nonlinear behaviour. Although the Decision Tree model offered superior interpretability, its predictive capability was comparatively lower, highlighting the trade-off between model transparency and accuracy.

Feature importance analysis confirmed that failure plane geometry and seismic loading are the primary factors governing slope stability. These findings align with established rock mechanics principles and reinforce the engineering validity of the developed surrogate models. From a practical perspective, the proposed framework enables rapid evaluation of multiple stability scenarios and supports probabilistic investigations that would otherwise require substantial computational resources. Machine learning models therefore represent an effective decision-support tool for preliminary design, sensitivity analysis, and risk-informed assessment in quarry environments.
Nevertheless, machine learning should be regarded as complementary to physics-based modelling rather than a substitute. While surrogate models significantly accelerate predictions, conventional numerical methods remain essential for detailed failure mechanism analysis and engineering verification.

Future research should focus on integrating high-resolution field data, expanding the parameter space, and exploring hybrid approaches that combine physics-based simulations with machine learning techniques. Such developments may further enhance predictive reliability and facilitate the broader adoption of data-driven methods in geotechnical engineering.

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