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A HYBRID ANN–FEM FRAMEWORK FOR HIGH ACCURACY SLOPE STABILITY PREDICTION

Purpose. To develop a hybrid methodology that integrates Artificial Neural Networks (ANN) with Finite Element Method (FEM) simulations for the rapid and accurate prediction of slope stability.

Methodology. A dataset of 1,000 FEM simulations was generated by systematically varying seven key input parameters: slope geometry (height and angle) and soil properties (cohesion, friction angle, unit weight, pore water pressure ratio, and reinforcement type). An ANN model with a (7-10-1) feedforward architecture was trained on this data.

Findings. The model demonstrated exceptional predictive performance, achieving a near-perfect correlation coefficient ($R \approx 0.999997$) and an extremely low mean squared error (MSE = $3.6828 \cdot 10^{-6}$), showing close agreement with the FEM-computed factors of safety (FOS). A comprehensive sensitivity analysis based on analysis of variance identified the pore water pressure ratio as the dominant controlling parameter, contributing approximately 77 % to the variability of FOS, followed by cohesion with a contribution of about 13 %. Complementary correlation analysis revealed that cohesion exhibits the strongest linear correlation with FOS ($r = 0.83$), whereas the pore water pressure ratio shows a relatively weak linear correlation, highlighting its pronounced nonlinear and interaction-driven influence on slope stability. These results demonstrate that the proposed ANN–FEM hybrid framework provides a powerful, efficient, and reliable tool for slope stability assessment and parametric analysis. The methodology is particularly well suited for engineering applications requiring rapid decision-making, large-scale evaluations, and uncertainty analysis.

Originality. The core originality of this research is its development of a robust ANN–FEM hybrid framework applied to a large, systematically generated dataset of 1,000 slope simulations. Unlike many studies, it comprehensively incorporates seven critical input variables, including the often underrepresented pore water pressure. Furthermore, its scientific rigor is enhanced by a dual interpretability strategy that combines analysis of variance for quantifying parameter contribution and correlation heatmaps for distinguishing linear effects from nonlinear ones, providing deeper insight into slope stability mechanisms.

Practical value. This study provides engineers with a fast and reliable tool to predict slope safety in seconds instead of running time-consuming FEM simulations, making it highly valuable for real-time decision-making and large parametric studies. Practically, it also shows that controlling pore water pressure (through drainage) is the most effective risk-reduction strategy, while cohesion offers a predictable way to improve slope stability in design.

Keywords: *slope stability, correlation analysis, finite element method (FEM), artificial neural network (ANN)*

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Introduction. Slope stability analysis is a fundamental challenge in geotechnical engineering, with direct implications for the safety and sustainability of civil infrastructure such as embankments, cut slopes, earth dams, and transportation corridors. Slope failures can lead to severe human, economic, and environmental losses, making accurate stability assessment a critical engineering requirement.

The stability of slopes is governed by a complex interaction of geometric, mechanical, and hydraulic fac-

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tors. Parameters such as cohesion, internal friction angle, unit weight, slope geometry, groundwater conditions, and reinforcement interact in a highly nonlinear manner. Traditionally, stability has been evaluated using limit equilibrium methods (LEM) and numerical techniques such as the finite element method (FEM). While these approaches are physically grounded, their application is often constrained by high computational cost, complex model calibration, and the need for precise input parameters that are inherently uncertain.

In recent years, artificial intelligence (AI) and machine learning (ML) techniques, particularly Artificial Neural Networks (ANNs), have emerged as powerful alternatives for slope stability evaluation. These data-driven models can capture complex nonlinear relationships between input parameters and stability outcomes, enabling rapid and accurate predictions of the factor of safety (FOS).

Previous research highlights the growing adoption of ANN and hybrid approaches in slope stability. Verma, et al. (2016) [1] proposed a pioneering hybrid FEM-ANN model for rock slopes in the Himalayan region. Building on this, Chakraborty and Goswami (2017) [2, 3] demonstrated the superiority of ANN over traditional regression methods using data generated via the simplified Bishop method. Pandey, et al. (2022) [4] further reinforced this approach, training deep learning models on a dataset of 185 slopes simulated with finite difference methods in Northern India. Their results reaffirmed the superior predictive accuracy of ANNs over conventional regression techniques.

More recent studies have explored advanced architectures and optimization algorithms. Huang, et al. (2023) [5] applied Long Short-Term Memory (LSTM) networks, while Khajehzadeh, et al. (2022) [6] combined ANN with an enhanced Sine Cosine Algorithm for slopes under static and dynamic loads. Similarly, Kasa, et al. (2024) [7] reported that an ANN hybridized with the Imperialist Competitive Algorithm (ANN–ICA) significantly outperformed standalone models. Additional works by Ray, et al. (2020) [8], Zhang and Wei (2025) [9], Wang, et al. (2024) [10], Dutta, et al. (2024) [11], and Zhang, et al. (2022) [12] have collectively validated the effectiveness and robustness of AI-driven approaches for slope stability prediction and parameter sensitivity analysis.

Despite these advances, most existing studies consider a limited set of controlling parameters and often lack emphasis on model interpretability and the relative influence of interacting factors. A notable limitation is the inadequate representation of hydraulic effects, particularly pore water pressure, and its interaction with mechanical and geometric parameters. Furthermore, sensitivity analyses are frequently based on a single technique, which may fail to capture nonlinear and interaction-driven effects, leading to incomplete interpretations.

To address these gaps, this study proposes a novel hybrid ANN–FEM framework that integrates high-fidelity numerical simulations with advanced data-driven modeling and a dual interpretability strategy. A comprehensive dataset of 1,000 FEM simulations was generated by systematically varying seven key parameters: slope height, slope angle, cohesion, internal friction angle, unit weight, pore water pressure ratio, and reinforcement type. This multi-parameter design enables a more realistic and exhaustive exploration of slope behavior than commonly reported.

Beyond predictive accuracy, the research introduces a comparative sensitivity framework combining analysis of variance-based contribution assessment with correlation heatmap evaluation. This approach distinguishes between parameters that dominate stability through nonlinear and interaction effects and those with strong linear relationships to the FOS. Special attention is given to the critical yet often underestimated role of pore water pressure, whose influence may not be fully captured by correlation analysis alone.

The primary scientific contribution of this work lies in integrating a physically grounded FEM dataset, a high-accuracy ANN predictive model, and a transparent sensitivity framework. By explicitly contrasting correlation and analysis of variance results within a unified hybrid approach, this study advances the understanding of slope stability mechanisms and provides a robust, efficient, and interpretable tool for engineering practice and future research.

Methodology. The methodology integrates FEM and ANN. The FEM model runs for multiple simulations, and the results feed the ANN model for training. The ANN rapidly analyzes data and generates predictions without returning to the computationally intensive finite element model. The ANN model also provides parameter information for efficient sensitivity analysis. Fig. 1 shows the general paradigm of the methodology.

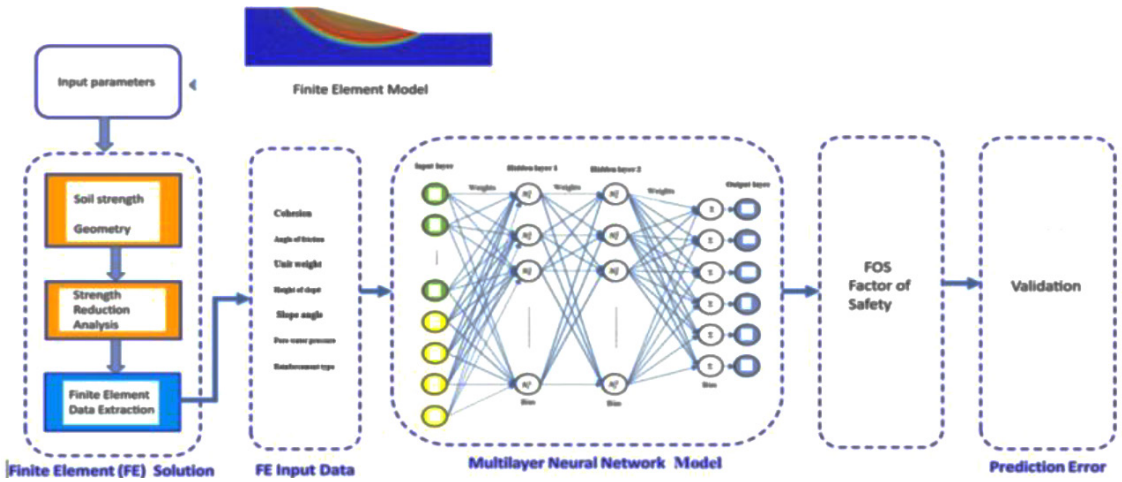

Fig. 1. General illustration of the proposed ANN-FEM integration for slope stability

Table 1

Parameter combinations and resulting FOS (20 of 1,000 cases was been shown)

No	Unit Weight, kN/m^3	Cohesion, kPa	Internal Friction Angle, °	Slope Angle, °	Slope Height, m	Pore Water Pressure Ratio	Reinforcement Type	Reinforcement Numerical Type
1	18.7454	21.81384	38.24996	41.90723	18.45104	0.847237	Drainage	3
2	24.50714	19.98104	24.6128	32.96462	9.2668	0.494517	Geosynthetics	2
3	22.31994	12.92693	28.66599	58.22493	10.68617	0.195466	Retaining Wall	0
4	20.98658	32.327	36.58202	20.94892	13.1302	0.736642	Drainage	3
5	16.56019	26.44809	32.05223	39.39282	14.1644	0.418678	Soil Nailing	1
6	16.55995	43.95654	38.46428	45.0105	15.90178	0.594627	Geosynthetics	2
7	15.58084	6.444931	44.0302	51.27822	16.4957	0.107265	Geosynthetics	2
8	23.66176	33.97406	22.91367	30.34855	25.50724	0.631584	Retaining Wall	0
9	21.01115	39.3327	37.73919	44.3461	27.93079	0.37355	Soil Nailing	1
10	22.08073	39.1769	25.7586	25.16007	18.89956	0.33419	Soil Nailing	1
11	15.20584	44.87333	30.36192	31.7738	45.82834	0.979916	Geosynthetics	2
12	24.6991	37.80652	20.82157	54.78136	29.89129	0.432431	Soil Nailing	1
13	23.32443	46.75145	23.39768	57.49538	40.43646	0.678038	Retaining Wall	0
14	17.12339	19.96955	27.99443	45.94087	46.5907	0.627728	Drainage	3
15	16.81825	27.64442	28.54965	28.71759	12.34108	0.104304	Soil Nailing	1
16	16.83405	5.633585	42.48963	51.00289	24.25435	0.747928	Retaining Wall	0
17	18.04242	5.313091	38.54532	11.29335	24.49447	0.323159	Geosynthetics	2
18	20.24756	15.8057	44.30457	15.1373	20.95125	0.79894	Drainage	3
19	19.31945	9.536324	34.97679	43.06869	5.400764	0.607641	Retaining Wall	0
20	17.91229	16.70951	26.04284	24.56243	41.71874	0.317091	Drainage	3

Material properties. The seven inputs (Unit Weight, Cohesion, Internal Friction Angle, Slope Angle, Slope Height, Pore Water Pressure Ratio, Reinforcement Type) were fed into the ANN, which was trained to predict the single output FOS. The Kaggle database system served as the source for the research dataset used in this study. Table 1 shows some representative data.

Each finite elements run produced a FOS, and these data were assembled into a training set for the neural network.

The ranges of the seven input parameters used for the slope stability analysis are presented in Table 2.

Design of computational experiments. The seven input parameters were varied simultaneously using Latin Hypercube Sampling (LHS), rather than full factorial design. A full factorial design would require $2^7 = 128$ simulations (only extreme values, missing intermediate behaviors), $3^7 = 2187$ simulations, or $4^7 = 16{,}384$ simulations – all of which are computationally prohibitive. LHS achieves uniform coverage of the 7-dimensional input space with only 1,000 simulations, while capturing nonlinear interactions between parameters (e.g., between pore water pressure and cohesion).

Because LHS is a continuous sampling method, there is no fixed step size. However, the approximate mean spacing for each continuous parameter is shown in Table 2. Reinforcement type was treated as a categorical variable with four discrete levels (Retaining Wall = 0, Soil Nailing = 1, Geosynthetics = 2, Drainage = 3), randomly assigned across the 1,000 simulations.

After generating the 1,000 combinations, a filtering step removed physically impossible combinations (e.g., very high cohesion combined with very high friction angle in the same soil). Less than 2 % of the initial combinations were discarded. Each remaining combination was then simulated using FEM to compute the corresponding FOS.

ANN Architecture. The ANN model was selected after testing numerous architectures. A feedforward backpropagation neural network was created using MATLAB's Neural Network Toolbox, consisting of 1 input layer with 7 neurons, 1 hidden layer with 10 neurons, and 1 output layer with 1 neuron (Figs. 2 and 3). In Fig. 3, W and b denote the weights and biases, respectively, which are learned during training.

Training protocol. The ANN is trained with the training data, while the test dataset is used to verify its

Table 2

The value ranges for the seven input parameters

Parameter	Range	Spacing
Unit weight, γ, kN/m^3	15.06–24.99	≈ 0.01
Cohesion, C, kN/m^3	5.10–49.91	≈ 0.045
Internal Friction Angle, φ, °	20.07–44.93	≈ 0.025
Slope angle, β, °	10.01–59.94	≈ 0.05
Slope Height, D, m	5.16–49.94	≈ 0.045
Pore Water Pressure Ratio	0.0006–0.9994	≈ 0.001
Reinforcement type	Retaining Wall, Soil Nailing, Geosynthetics, Drainage	Categorical

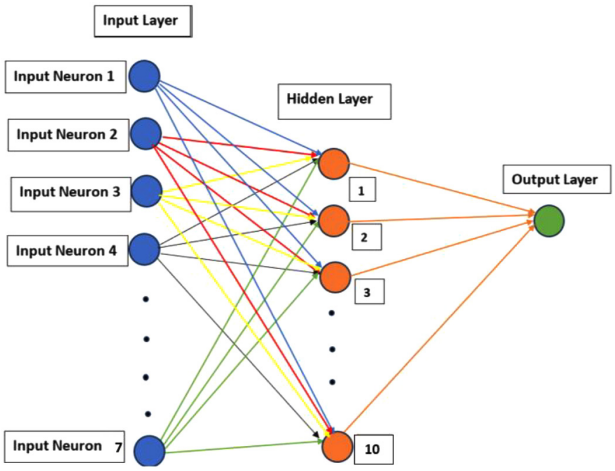

Fig. 2. Feed forward back-propagation neural network architecture

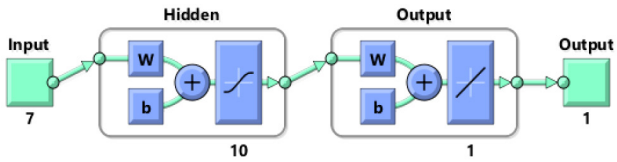

Fig. 3. Architecture of the ANN

predictive performance along with the validation dataset. In this study, 70 % of the total data is used for the training dataset, 15 % for the test dataset, and 15 % for validation. The Levenberg-Marquardt algorithm is used to train the neural networks, and the mean square error is minimized during the training process (This algorithm typically requires more memory but less time). Training automatically stops when generalization stops

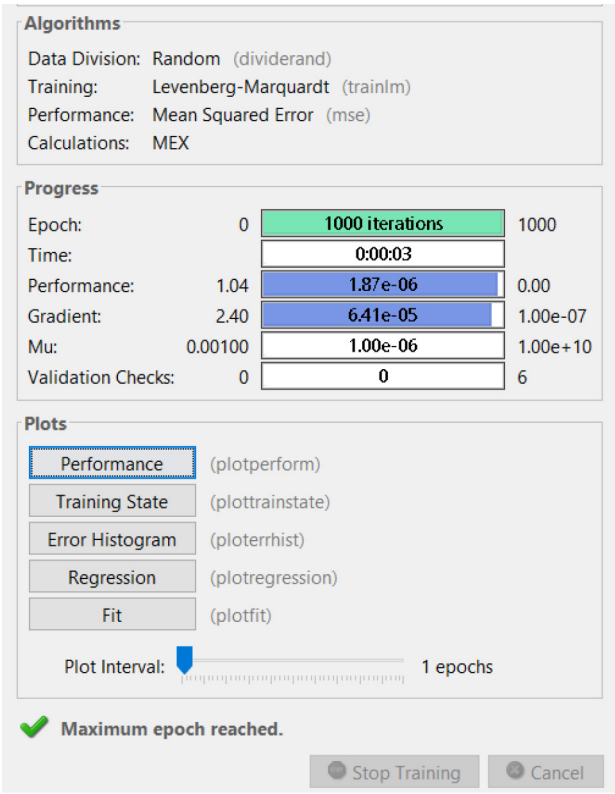

Fig. 4. Results of Training Data

improving, as indicated by an increase in the mean square error of the validation samples. Dataset errors were determined after network training, using the mean square error (MSE) to measure errors. The test set errors provide an indication of the network's performance.

Findings. The training results (Fig. 4) show that the best performance is 1.04, with a performance error of $1.87 \cdot 10^{-6}$, significantly lower than the target error of 0.001. The gradient value was 2.40, with a training gain (Mu) of 10^{-6}. One validation check was recorded. For 1,000 epoch iterations, the computation time was three seconds.

The performance evaluation plot (Fig. 5) shows the training algorithm's progress. The objective was met by minimizing MSE to $3.6828 \cdot 10^{-6}$ at 1,000 epochs. The test set MSE values shown in Fig. 5 were computed at each epoch using the current model state, but these values did not influence weight updates or early stopping decisions. The test set was kept completely unseen during training and used only for independent performance monitoring. This is standard practice for assessing generalization across epoch.

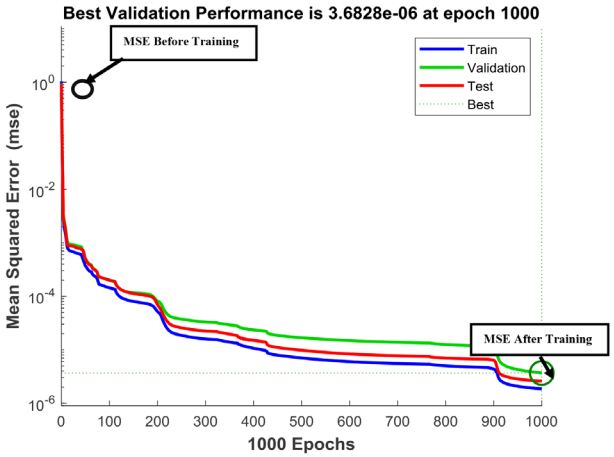

Fig. 5. Performance plot of the developed neural network mode

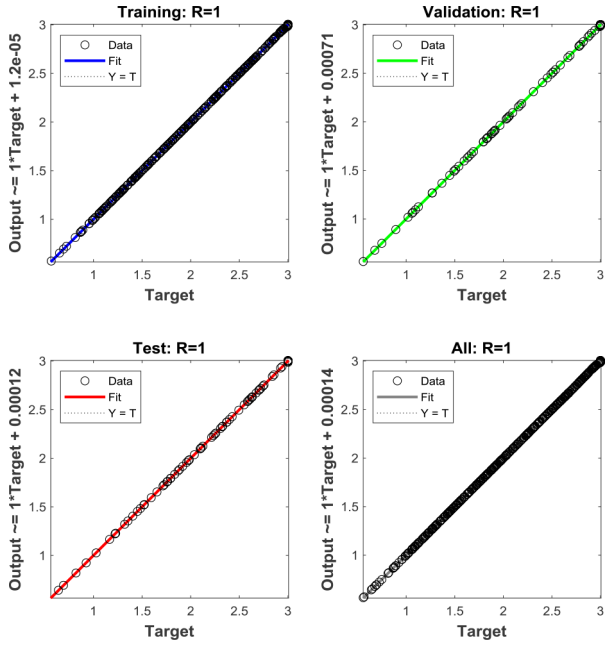

Fig. 6. Targeted and output factor of safety by ANN for training, validation and test data

In this graph (Fig. 5), the blue line indicates the training state, while the green and red lines indicate the validation and testing states. The dashed black line indicates the most expected output state.

Mean square errors plotted against epochs during optimal network training show values close to zero, indicating good estimators.

Fig. 6 was generated after training completion. For each training sample (n = 700), the predicted FOS from the trained ANN is plotted against the target FOS from FEM simulation. The red diagonal line ($Y = T$) indicates perfect prediction. This plot is a post-training visualization and does not influence the training process. The high performance of the trained neural network is confirmed by the correlation coefficient R being very close to 1 (approximately 0.99999). The convergence of the regression output and target results is also evident from Fig. 7, which is a testament to the network's robust performance.

Regression Values (R) measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 – a random relationship. Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2. \quad (1)$$

Equation (1) shows the mathematical formulation of MSE, where y is the measured value; $\hat{y}$ is the predicted value; N is the number of the sample [13].

To demonstrate the excellent predictive performance of the model, Table 3 summarizes the key metrics of R and MSE for the training, validation, and testing datasets.

The error histogram (Fig. 7) shows most errors gathered around zero, confirming appropriate training method selection and acceptable outcomes.

Table 3

The values of R and MSE in different states

	Samples	MSE	R
Training	700	$1.86500 \cdot 10^{-6}$	0.999997
Validation	150	$3.68283 \cdot 10^{-6}$	0.999995
Testing	150	$2.59457 \cdot 10^{-6}$	0.999996
Overall	1,000	$2.28016 \cdot 10^{-6}$	0.999997

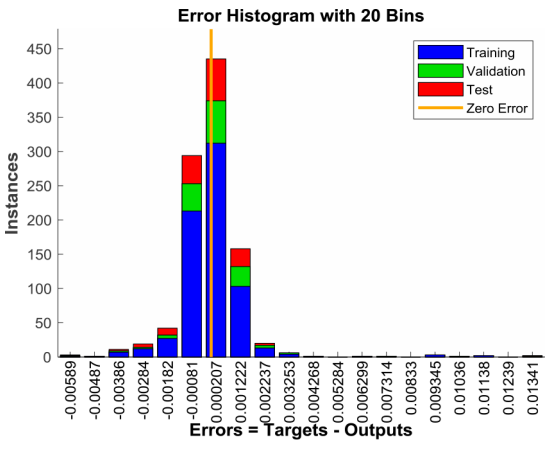

Fig. 7. Error histogram for training, validation and testing for FSO

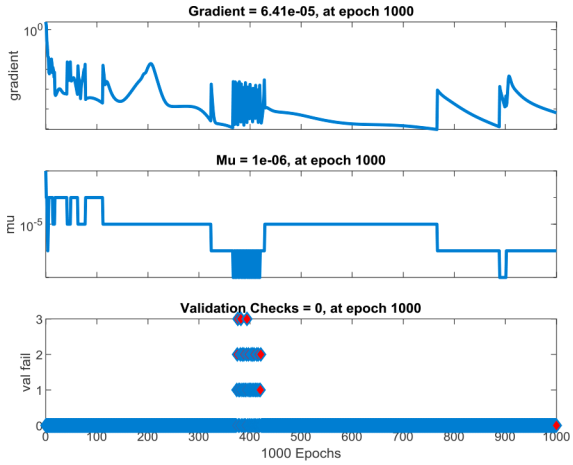

Fig. 8. Plotting the gradient values, mu and validation fail

Fig. 8 shows gradient values, mu, and validation fail parameters. The calculated gradient value of $6.41 \cdot 10^{-5}$ at epoch 1,000 indicates minimal error contribution from each neuron. The momentum gain of 10^{-6} shows the network's high predictive ability.

Prediction accuracy. Table 4 compares PLAXIS-derived FOS to ANN-predicted FOS for 50 sample runs

The results compare the FOS calculated using two different methods: the Finite Element Method, and Artificial Neural Network, which is a predictive model. The primary goal is to assess the accuracy and reliability of the ANN model in predicting the FOS.

The ANN model demonstrates high accuracy, with prediction errors for the Factor of Safety generally falling within a 0–1.98 % range; most errors are below 0.5 % in absolute value, and for runs where the finite element method yields a FOS of 3.0 or less, the ANN predictions are consistently very close to the reference results, with only a small number of cases showing slightly larger but still reasonable errors between 0.5–1 %.

Fig. 9 shows predicted data largely coinciding with target data from finite element analyses, validating ANN's ability to quickly estimate slope safety factors.

From Fig. 9, the red line indicating the predicted data which largely coincides with the blue line indicating the target data obtained from the finite element analyses.

Fig. 10 presents the values of the coefficient of determination R^2, which validate the performance of the ANN model predictions. The obtained R^2 value of 0.9995 indicates that the ANN model has a high ability to predict FOS values from the data used in the 2D FEM analysis, and highlights a strong correlation between the ANN results and the 2D FEM targets [14].

FOS_{FEM} and FOS_{ANN} is presented in Table 4.

Sensitivity analysis. Table 5 shows the results of the sensitivity analysis, which quantifies the relative influence of each input parameter on the predicted Factor of Safety. The analysis reveals that Pore Water Pressure Ratio is the overwhelmingly dominant driver, accounting for 76.93 % of the variation in FOS predictions. This single parameter has more influence than all other factors combined. Among the secondary parameters, Cohesion (C) is the most significant, contributing 12.97 %, followed by the Internal Friction Angle (φ) at 4.62 %. The other geometric and material parameters: Unit

Table 4

FEM vs. ANN comparison (50 of 1,000 cases was been shown)

Run	FOS (FEM)	FOS (ANN)	% Error (FOS)
1	2.613692	2.6079	–0.22159
2	2.241626	2.2467	0.226338
3	1.568244	1.5624	–0.37262
4	3	3	0
5	3	2.9985	–0.05
6	3	3	0
7	1.545751	1.5438	–0.12625
8	3	3	0
9	3	3	0
10	3	3	0
11	3	3	0
12	3	3	0
13	3	3	0
14	2.15683	2.164	0.332432
15	3	3	0
16	1.095687	1.0941	–0.14483
17	1.54164	1.542	0.023346
18	2.506546	2.4961	–0.41676
19	1.385018	1.3869	0.135879
20	2.134876	2.1383	0.160389
21	1.482568	1.4788	–0.25414
22	0.877753	0.86033	–1.98492
23	3	3	0
24	0.991259	0.98419	–0.71313
25	3	3	0
26	1.441251	1.4421	0.058889
27	3	3	0
28	3	3	0
29	3	3	0
30	3	3	0
31	1.104977	1.1064	0.128818
32	3	3	0
33	3	3	0
34	3	3	0
35	3	2.9998	–0.00667
36	2.928341	2.9349	0.22399
37	3	3	0
38	2.21411	2.2187	0.207322
39	3	3	0
40	1.312585	1.3165	0.29826
41	3	3	0
42	1.935005	1.9344	-0.03127
43	2.399988	2.4017	0.071316
44	3	3	0
45	3	3	0
46	3	3	0
47	2.142138	2.1452	0.142947
48	0.640311	0.65296	1.9754
49	3	3	0
50	3	3	0

Weight (γ), Slope Angle (β), Slope Height (*D*), and Reinforcement Type have minimal individual influence, each contributing less than 2.1 %.

Therefore, while soil strength (*C*, ϕ) and geometry are relevant, the model's predictions are primarily and decisively sensitive to changes in pore water pressure conditions.

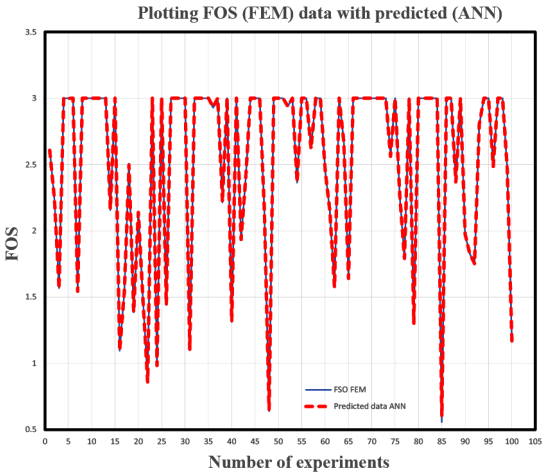

Fig. 9. Plotting FOS (FEM) data with predicted (ANN)

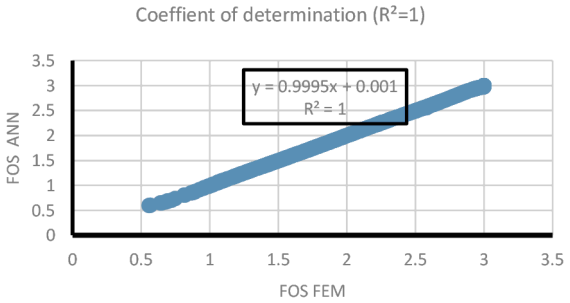

Fig. 10. Coefficient of determination between values obtained by ANN and FEM

Table 5

Contribution of parameters

Parameter	Contribution %
Unit weight, γ	2.08
Cohesion, *C*	12.97
Internal Friction angle, φ	4.62
Slope angle, β	1.16
Slope Height, *D*	0.67
Pore Water Pressure Ratio	76.93
Reinforcement type	1.56

The pore water pressure ratio has the highest contribution (≈77 %) to the factor of safety, making it the most influential parameter in this dataset. Even a small change in this parameter causes a dramatic shift in the FOS. This is perfectly consistent with soil mechanics principles: water pressure reduces the effective stress in the soil, which drastically diminishes shear strength and, consequently, the FOS. Cohesion follows with about 13 %, while the other parameters (friction angle, unit weight, and reinforcement type, slope angle, slope height) have relatively minor effects on slope stability.

Correlation analysis (Heatmap). Fig.11 presents the correlation heatmap which displays the relationship between geotechnical parameters (unit weight, cohesion, angle of internal friction, angle of slope, height of slope, pore pressure ratio, number of reinforcements) and factor of safety.

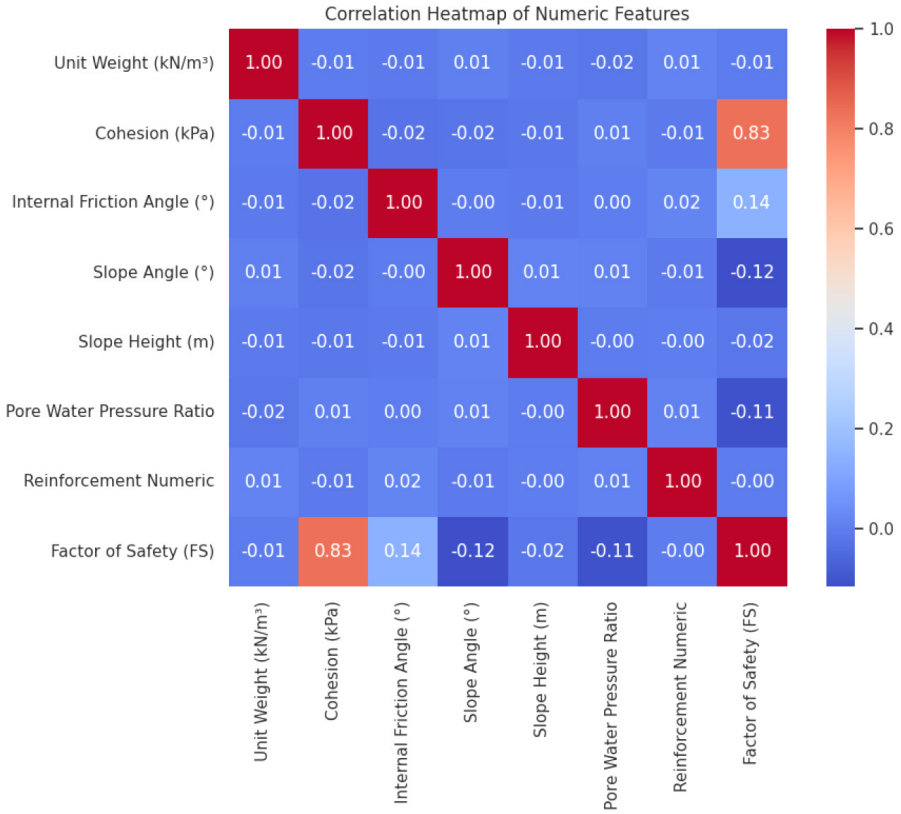

Fig. 11. Correlation heatmap of geotechnical parameters and slope safety

The most pronounced positive correlation, at 0.83, exists between cohesion and the FOS, indicating that soils with higher cohesion significantly enhance slope stability.

Meanwhile, the internal friction angle (φ) shows a modest positive correlation of 0.14, suggesting that increases in φ only marginally improve the FOS.

Other parameters such as unit weight, slope angle, slope height, pore water pressure ratio, and reinforcement type exhibit very weak or negligible correlations ($|r| < 0.12$), implying limited direct influence on FOS in this dataset.

Overall, the strong positive impact of shear strength parameters underscores their critical role in stabilizing slopes [15]. On the other hand, negative correlations (such as slope height, slope angle, and pore pressure) reflect destabilizing effects: steeper or taller slopes amplify driving forces, while higher pore pressures reduce effective stress and thus shear resistance, there by undermining slope safety.

Comparison and Synthesis sensitivity analysis and correlation analysis heatmap (Table 6).

The sensitivity analysis based on analysis of variance and the correlation analysis provide complementary, rather than contradictory, insights into the influence of input parameters on slope stability. Each method captures a different aspect of the relationship between the geotechnical variables and the predicted Factor of Safety.

The analysis of variance-based sensitivity analysis quantifies the relative contribution of each input parameter to the variance of the predicted FOS within the ANN model, accounting for linear effects, non-linear behavior, and interactions between variables. The results indicate that the pore water pressure ratio is the most influential parameter, contributing approximately 77 % of the total variance. This highlights its critical role as the primary driver of slope instability, where even small variations can induce large and non-linear changes in the FOS. Cohesion follows as the second most influential parameter, with a contribution of about 13 %, while the remaining parameters exhibit comparatively minor contributions.

In contrast, the correlation analysis evaluates only the strength of linear relationships between individual parameters and the FOS. From the correlation heatmap, cohesion shows the strongest positive linear correlation with FOS (r = 0.83), indicating a direct and

Table 6

Comparison and Synthesis sensitivity analysis and correlation analysis heatmap

Feature	Sensitivity Analysis	Correlation Analysis (Heatmap)
Interpretation for Pore Water Pressure	High Importance (≈77 %): It is the most "influential" or "sensitive" parameter. It is the main driver of changes in FOS	Weak Correlation (= –0.11): Its effect on FOS is not a simple straight line. It is complex and non-linear
Interpretation for Cohesion	High Importance (≈13 %): The second most influential parameter	Strong Correlation (0.83): Its effect on FOS is linear and direct. It is a reliable, predictable predictor

predictable stabilizing effect. Conversely, the pore water pressure ratio exhibits a weak negative linear correlation ($r = -0.11$), despite its dominant contribution in the sensitivity analysis.

This apparent discrepancy is not contradictory but rather reveals the fundamentally different roles of the parameters. The pore water pressure ratio influences slope stability primarily through complex, non-linear mechanisms and interactions with other variables, which are effectively captured by the analysis of variance-based sensitivity analysis but not by simple linear correlation. In contrast, cohesion acts as a reliable and linearly predictable parameter, making it an effective design variable for systematically improving slope stability.

Overall, the combined use of sensitivity analysis and correlation analysis enhances the interpretability of the ANN model by distinguishing between parameters that are highly sensitive and risk-critical (such as pore water pressure) and those that exert a strong and predictable stabilizing influence (such as cohesion). This dual perspective provides a more comprehensive understanding of slope stability mechanisms and supports more informed engineering decision-making.

Conclusion. This study successfully developed and validated a hybrid ANN–FEM computational framework for slope stability analysis that combines the physical rigor of the Finite Element Method with the predictive efficiency of Artificial Neural Networks. A 7-10-1 feed-forward backpropagation ANN was trained using a comprehensive dataset of 1,000 FEM simulations and demonstrated outstanding predictive performance, achieving a near-perfect correlation coefficient ($R \approx 0.999997$) and a very low mean squared error ($\mathrm{MSE} = 3.6828 \cdot 10^{-6}$). These results confirm the model's ability to accurately reproduce FEM-derived factors of safety while reducing computational time from hours to seconds, making it highly suitable for rapid assessments and large-scale parametric studies.

Sensitivity results indicate that slope stability within the investigated parameter ranges is predominantly governed by pore water pressure conditions, followed by soil cohesion, while geometric parameters such as slope angle and height exert a comparatively smaller influence. From an engineering perspective, these findings highlight the critical importance of groundwater management and effective drainage systems as primary risk-mitigation measures. At the same time, improvements in soil cohesion provide a reliable and practical means of enhancing slope stability during design and reinforcement planning.

Overall, the proposed ANN–FEM framework offers an efficient, accurate, and interpretable tool for rapid slope safety evaluation and informed engineering decision-making. By enabling both high-fidelity prediction and clear prioritization of key stability drivers, the methodology represents a valuable contribution to modern geotechnical practice. Future extensions to three-dimensional configurations and dynamic loading conditions are expected to further expand the applicability of the proposed approach.

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Гібридна методика ANN–FEM для високоточного прогнозування стійкості схилів

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Мета. Розробка гібридної методики, що поєднує штучні нейронні мережі (ANN) із моделюванням методом скінченних елементів (FEM) задля швидкого й високоточного прогнозування стійкості схилів.

Методика. Було сформовано набір даних, що містив 1 000 результатів моделювання методом кінцевих елементів, шляхом систематичної зміни семи основних вхідних параметрів: геометрії схилу (висота й кут нахилу) та властивостей ґрунту (когезія, кут тертя, питома вага, коефіцієнт порового тиску й тип армування). На основі цих даних було навчено модель штучної нейронної мережі з архітектурою прямого поширення сигналу (7-10-1).

Результати. Модель продемонструвала винятковy прогностичну ефективність, досягнувши майже ідеального коефіцієнта кореляції ($R \approx 0{,}999997$) і надзвичайно низької середньоквадратичної похибки ($MSE = 3{,}6828 \cdot 10^{-6}$), що свідчить про високу збіжність із коефіцієнтами запасу стійкості (FOS), розрахованими методом кінцевих елементів (FEM). Комплексний аналіз чутливості, заснований на дисперсійному аналізі, визначив коефіцієнт порового тиску як домінуючий контролюючий параметр, що забезпечує приблизно 77 % варіації коефіцієнта запасу стійкості FOS, за яким слідує когезія із внеском близько 13 %. Додатковий кореляційний аналіз показав, що когезія демонструє найсильнішу лінійну кореляцію з коефіцієнтом запасу стійкості FOS ($r = 0{,}83$), тоді як коефіцієнт порового тиску демонструє відносно слабку лінійну кореляцію, що підкреслює його виражений нелінійний та обумовлений взаємодією вплив на стійкість схилу. Ці результати свідчать про те, що запропонована гібридна модель ANN–FEM є потужним, ефективним і надійним інструментом для оцінки стійкості схилів і параметричного аналізу. Ця методологія особливо добре підходить для інженерних завдань, що вимагають швидкого прийняття рішень, масштабних оцінок й аналізу невизначеності.

Наукова новизна. Основною науковою новизною дослідження є розробка надійної гібридної моделі на основі штучних нейронних мереж (ANN) і методу скінченних елементів (FEM), побудованої на великому систематично сформованому масиві даних, що включає 1 000 моделей схилів. На відміну від багатьох досліджень, у ньому всебічно враховано сім ключових вхідних змінних, зокрема тиск порової води. Крім того, наукова обґрунтованість цього підходу підкріплюється стратегією подвійної інтерпретації, що поєднує аналіз дисперсії для кількісної оцінки внеску параметрів і теплові карти кореляції для розрізнення лінійних і нелінійних ефектів, що дає змогу глибше зрозуміти механізми стійкості схилів.

Практична значимість. Це дослідження надає інженерам швидкий і надійний інструмент для прогнозування стійкості схилів за лічені секунди замість проведення тривалих моделювань методом кінцевих елементів, що робить його надзвичайно цінним для прийняття рішень у режимі реального часу та проведення масштабних параметричних досліджень. На практиці воно також демонструє, що регулювання порового тиску (за допомогою дренажу) є найефективнішою стратегією зниження ризиків, тоді як когезія забезпечує прогнозований спосіб підвищення стійкості схилів на етапі проєктування.

Ключові слова: *стійкість схилів, кореляційний аналіз, метод скінченних елементів (FEM), штучна нейронна мережа (ANN)*