A Neural Network-Based Deployable Model for Estimation of Slope Factor of Safety

Syed Saarim Ahmad

Executive Engineer, Mine Planning, NLCIL, Neyveli, India

Abstract - *Determination of slope factor of safety (FoS) is a critical step in the evaluation of slope stability. Conventional methods for FoS determination such as the limit equilibrium method (LEM) and finite element method (FEM) are time consuming and require high computational power and costs. Machine learning tools such as artificial neural networks (ANN) can be utilized to overcome these challenges. This study presents an ANN model for rapid determination of slope FoS. The model takes in five input parameters: slope height, slope angle, material density, cohesion and the angle of internal friction to estimate the FoS. A dataset of 900 slope models was generated using the LEM covering a wide range of input parametric values for training and testing the model. Model architecture was optimized by varying the network hyper-parameters. The final optimized model consisting of two hidden layers with a 5-50-50-1 architecture shows strong predictive capability with a testing root-mean-squared-error (RMSE) of 0.054 and coefficient-of-determination (R2) of 0.981. The model was deployed as a web-based application to enable practical field-based implementation. Further, the model was field-validated using geotechnical and slope geometry data from a real opencast lignite mine case study. The model-derived slope factor of safety values showed close agreement with LEM-derived reference values, with percentage errors ranging between 0.92% and 3.33% as compared to LEM-derived values, thereby confirming the model's reliability for practical field-based use. The model drastically reduces time and effort needed to perform slope stability analyses whilst preserving accuracy.*

Key Words: artificial neural network, slope factor of safety, limit equilibrium method, slope stability.

1. INTRODUCTION

Slope failure incidents have resulted in significant loss of life and property across the world. While there are an abundant number of sophisticated slope stability analytical software more suited for case studies and detailed slope simulation [1], there is a lack of user-friendly tools that can be readily used in the field by mining professionals to obtain instantaneous factor of safety (FoS) values based on simple parametric inputs. The availability of such a tool would enable mine operators to quickly assess the prevailing slope stability conditions during routine operations. Conventional methods for FoS determination generally require high computational effort and are resource-intensive [2]. Therefore, a simple, portable tool capable of accurately and instantaneously predicting slope factor of safety would have substantial potential for application within the mining and civil engineering industries for preliminary slope stability assessment.

A neural network is a machine learning tool that mimics the biological structure of the human brain and is capable of "learning" from existing data to identify underlying patterns [3]. When suitably trained, neural networks are highly effective predictive tools and can model complex non-linear relationships with considerable accuracy.

This study presents an artificial neural network (ANN) model for rapid, field-based determination of slope factor of safety with high predictive accuracy. A total of 900 datasets were used in the study, of which 810 datasets were allocated for training and 90 datasets for testing, maintaining a training-to-testing ratio of 9:1. The trained model achieved a testing root-mean-squared-error (RMSE) of 0.054, and coefficient of determination (R2) of 0.981. The proposed model is not intended to replace conventional methods of factor of safety determination; rather, it is envisioned as a preliminary analytical tool to provide a rapid indication of slope stability conditions in mining operations.

The effect of modifying the network architecture (number of nodes per hidden layer) on the predictive performance of the model is analysed. Based on this analysis a 5-50-50-1 network architecture is selected that optimizes model accuracy, complexity and training time. The model was then deployed as a web-based application. The application enables practical implementation of the model as a preliminary field-based tool to rapidly iterate between slope scenarios and screen the safest slope configuration in a time efficient and economical manner. The selected slope configuration can then be validated using FEM or LEM.

2. LITERATURE REVIEW

Slope stability analysis has traditionally been carried out using analytical and numerical approaches, with the limit equilibrium method (LEM) being the most widely adopted technique in engineering practice [4]. The limit equilibrium method is the oldest method for determining the factor of safety of slopes. It is purely based on the principle of statics, in which the force and/or moment equilibrium must be satisfied [5, 6]. For example, Fellenius' method satisfies the moment equilibrium condition but not the force equilibrium condition. Bishop's method satisfies the moment equilibrium and vertical force equilibrium conditions but not the horizontal force equilibrium condition. Spencer's method is a more rigorous method that satisfies all three conditions of equilibrium: horizontal and vertical force equilibrium and moment equilibrium [7]. All three methods assume a circular slip surface [7]. The Bishop's method has been widely accepted as one of the best methods of limit equilibrium for calculating the factor of safety of circular slip surfaces [8].

In recent years, machine learning techniques such as neural networks have gained increasing attention in geotechnical engineering due to their ability to model complex non-linear relationships between multiple input parameters and system responses [9-11]. Neural networks can broadly be classified into three types: artificial neural networks (ANN), convolutional neural networks (CNN), and recurrent neural networks (RNN). ANNs in particular, have been successfully applied to problems such as soil classification [12], bearing capacity prediction [13], settlement estimation [14], and slope stability assessment [9-11]. These studies successfully demonstrate the potential of ANN models to approximate complex geotechnical relationships; however, their interpretability and field applicability remain limited. Several researchers have explored the use of ANN models for predicting slope factor of safety based on geometrical and geotechnical parameters [9-11]. These studies have demonstrated that neural networks can achieve prediction accuracies comparable to conventional methods [9-11].

3. METHODOLOGY

3.1 DATA GENERATION

A total of 900 distinct slope models were generated by systematically varying five key geotechnical and geometrical parameters, namely slope height (h), slope angle (β), material density (ϒ), cohesion (c) and angle of internal friction (φ). These parameters were selected based on their well-established influence on slope stability and their widespread use in conventional slope stability analyses. The ranges and intervals adopted for each parameter are presented in Table 1, ensuring adequate coverage of both stable and marginally unstable slope conditions.

Table -1: Ranges of input parameters, step size and number of distinct values of each parameter

Parameter	Minimum value	Maximum value	Step size	Number of values	Maximu m value	Step size
Slope height (h)	20 m	60 m	10 m	5	60 m	10 m
Slope angle (β)	30°	45°	5°	4	45°	5°
Bulk Density (ϒ)	1500 kg/m3	2500 kg/m3	500 kg/m3	3	2500 kg/m3	500 kg/m3
Cohesion (c)	20 kPa	60 kPa	10 kPa	5	60 kPa	10 kPa
Angle of internal friction (φ)	20°	30°	5°	3	30°	5°

For each simulated slope configuration, the factor of safety (FoS) was computed using the limit equilibrium method (LEM). The LEM-based FoS calculations were carried out using HYRCAN geotechnical software. A representative slope geometry used in the simulations is illustrated in Fig. 1, showing the assumed slope profile and boundary conditions adopted for the analysis.

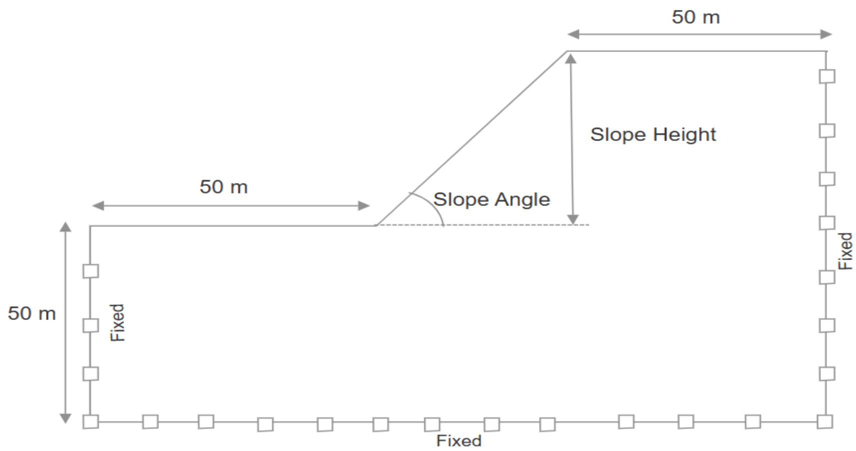

Fig -1: Schematic representation of a slope geometry

The resulting dataset comprises paired input–output samples, where the five input parameters correspond to a single FoS value obtained from LEM analysis. Out of the total of 900 generated datasets generated, 810 were randomly selected for training the model and the remaining 90 datasets for testing. The full dataset comprising 900 observations is provided as a supplementary file (see Supplementary Table S1).

3.2 BUILDING THE ARTIFICIAL NEURAL NETWORK (ANN)

The homogeneous slope considered in this study is represented by five key independent input parameters, namely slope height (h), slope angle (β), bulk density (γ), cohesion (c), and angle of internal friction (φ). These parameters constitute the input nodes of the neural network. The neural network was developed using the Python programming language implementing the TensorFlow library. It is common practice to normalize the input parameters before propagating them through the network [15]. The formula used for normalization of the input parameters is given in Eq. (1).

$$x'_i = \frac{(x_i - x_{\min})}{(x_{\max} - x_{\min})} \tag{1}$$

where, x'_i is the normalized value of x_i, x_{max} is the maximum value of the parameter and x_{min} is the minimum value of the parameter. The network architecture consists of an input layer of 5 neurons followed by two fully connected hidden layers and a single-node output layer for giving the FoS value. Each hidden layer employs the rectified linear unit (ReLU) activation function to introduce non-linearity and enhance the model's ability to learn complex relationships between input parameters and FoS. The network weights and biases were adjusted using the stochastic gradient descent (SGD) method of optimization with mean square error (MSE) as the loss function. The final network architecture was determined following an iterative process of adjusting network hyper-parameters as described in section 3.3.

3.3 TRAINING THE MODEL

To optimize the neural network architecture, an iterative method was followed in which the number of neurons in the hidden layers were varied between 1 and 50 in steps of 5 and training RMSE was determined for each case. RMSE was calculated as per Eq. (2).

$$RMSE = \sqrt{\frac{\sum_{i=0}^{n}(x_i - y_i)^2}{n}} \tag{2}$$

where, RMSE denotes Root-Mean-Squared-Error, xi is the ith value of 'true' FoS, y_i is ith value of predicted FoS and n is the number of datasets.

This procedure was repeated for each case by adjusting the number of epochs as well (between 20 and 100 epochs in steps of 20). Training RMSE were noted in each step and were plotted against number of nodes in hidden layer for each epoch run (Fig. 2).

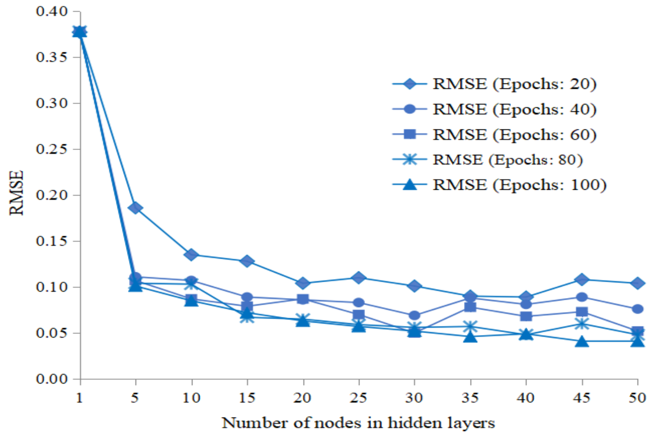

Fig -2: Plot of RMSE and number of nodes in hidden layers for each epoch run

The curve shows an inverse relationship between number of nodes and RMSE, with RMSE improving as number of nodes are increased, however, improvements diminished beyond network size of 50 neurons. It is noted that increasing the number of epochs significantly improves the network accuracy.

An optimized neural network of 5-50-50-1 architecture with 50 neurons in each hidden layer was selected as the final model following the principle of diminishing returns. To avoid over-fitting, the number of epochs was limited to 100. The trained model with 5-50-50-1 architecture was preserved and served as a surrogate model for application development. A schematic representation of the finalized neural network architecture is shown in Fig. 3.

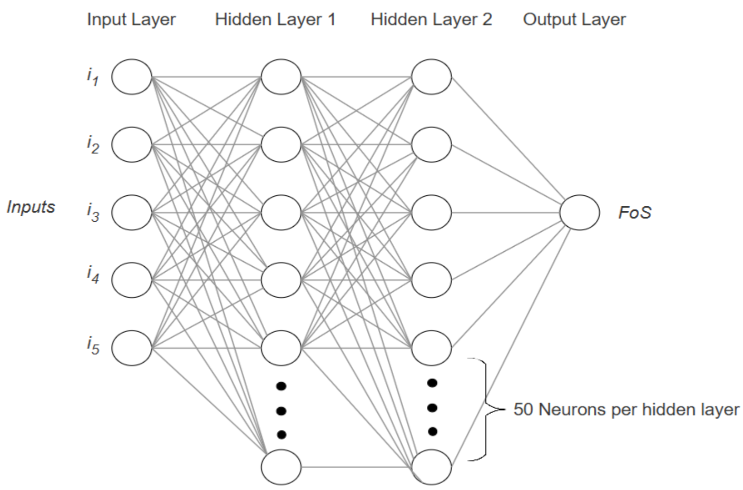

Fig -3: Schematic representation of the ANN model

3.4 APPLICATION DEVELOPMENT

To facilitate practical implementation and real-time use, the trained neural network model was deployed as a web-based application using Streamlit framework [16]. The application provides an interface that allows users to input slope geometry and material parameters and obtain instantaneous predictions of the slope factor of safety. The trained ANN model is integrated within the application back-end, ensuring consistency between the model used for analysis and the deployed tool [17].

4. RESULTS, VALIDATION AND DISCUSSION

4.1 TESTING THE MODEL

The trained model was then tested using 90 datasets. It was observed that the trained model achieves a testing RMSE of 0.054, which demonstrates an excellent predictive accuracy of the model. The table consisting of 90 input datasets along with ANN derived FoS values, absolute errors, squared errors and RMSE is provided as a supplementary file (see Supplementary Table S2). The trained model achieved a coefficient of determination (R2) of 0.981 as shown by the scatter plot in Fig. 4.

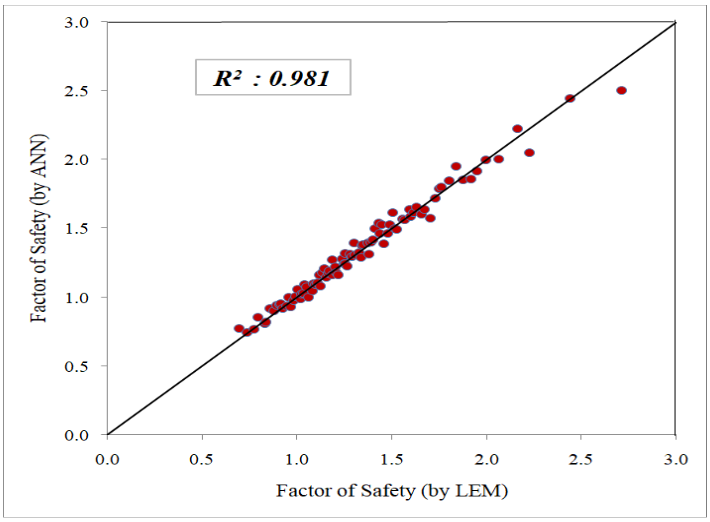

Fig -4: Scatter plot of ANN versus LEM derived FoS values showing the coefficient of determination (R^2)

The results show that the trained model with a 5-50-50-1 architecture displays strong predictive capability with the predicted FoS values being in close conformity with the LEM-derived FoS values.

4.2 VALIDATION USING REAL MINE EXAMPLE

4.2.1 BACKGROUND

NLC India Ltd. (NLCIL) operates three large opencast lignite mines in the Neyveli region of Tamil Nadu. All three mines are mechanized operations using the bucket wheel excavator (BWE)–conveyor system. Mine II is the largest of the three, with a peak rated production capacity of 13.0 million tonnes of lignite per year. Mine II follows an in-pit dumping system in which the excavated overburden is deposited into the void created by lignite extraction. The in-pit dump comprises five benches, with individual bench heights ranging from approximately 20 m to 65 m and a cumulative dump height of approximately 120 m. The dump material, known colloquially as "Cuddalore sandstones", consists of granular sedimentary deposits composed of sand, silt, and clay in varying proportions and can be broadly classified as sandy loam. The strata are free of structural discontinuities such as folds and faults, making the dump slopes suitable for analysis by the limit equilibrium method with a circular failure surface and homogeneous material properties.

A prior slope stability study conducted on a three-benched region within the eastern portion of the Mine II overburden dump [4] provides the geotechnical and geometrical data used for field verification of the ANN-based application in the present study. Fig. 5 shows the schematic part plan of Mine dump region of interest along with cross sections marked 1-1' to 3-3'.

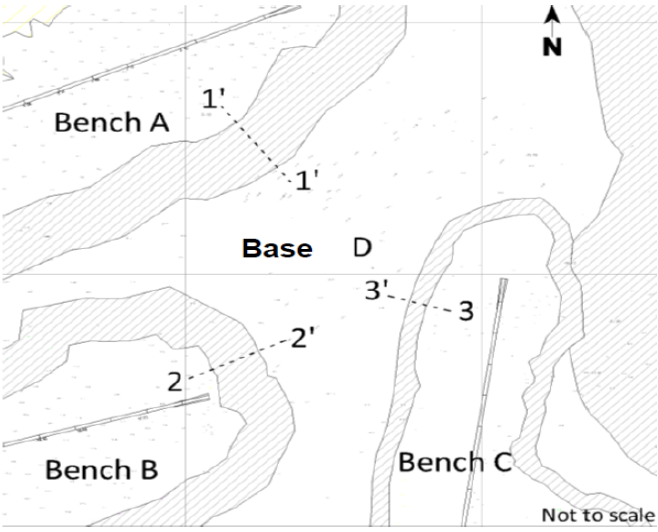

Fig -5: Part plan showing dump region along with cross sections [4].

The three dump benches analyzed in the study, designated as Bench A, Bench B, and Bench C, have bench heights of 68 m, 55 m, and 22 m respectively, with slope angles in the range of 37°–39°. Their undrained shear strength properties were determined from unconsolidated undrained triaxial tests (Q tests) on disturbed soil samples retrieved from the respective benches [4]. Geotechnical testing showed that Material density across the samples ranged from 1.82 to 1.90 g/cc, cohesion ranged from 56 to 64 kPa, and the angle of internal friction was consistently in the range of 23°–24° [4]. Table 2 shows the geotechnical and geometrical parameters for the three slopes. The LEM-derived factor of safety values from the study serves as the reference "true" values against which the ANN application predictions are compared in this case study.

Table -2: Geotechnical and geometrical parameters of the three slopes of Mine II.

Slope (Bench)	Bench Height (m)	Slope angle (°)	Material density (g/cc)	Cohesion (kPa)	Angle of internal friction (°)
1-1' (A)	68	37°	1.84	60	24
2-2' (B)	55	39°	1.82	56	24
3-3' (C)	22	38°	1.88	62	24

4.2.2 LEM-BASED SLOPE STABILITY ANALYSIS

To establish the reference benchmark for this validation exercise, the slope stability of the three Mine II dump benches was evaluated using the limit equilibrium method (LEM) via HYRCAN 2-D geotechnical software, following the procedure described in prior slope stability study [4]. The factor of safety was determined using Bishop's simplified method and Spencer's method, both assuming a circular slip surface. The effect of groundwater was neglected, consistent with field conditions, as no water table was observed within the body of the dump.

The LEM-derived FoS values as established in [4] are reproduced in Table 3 for reference. Benches A and B returned FoS values of 1.187 and 1.200, respectively (Bishop's method), classifying them as moderately stable (1.0 ≤ FoS < 1.3). Bench C returned an FoS of 1.923, classifying it as highly stable (FoS ≥ 1.3). These values form the ground-truth reference for the subsequent comparison with the ANN application outputs.

4.2.3 COMPARISON WITH APPLICATION-DERIVED FOS

The slope parameters and soil shear strength properties of the three Mine II dump benches were entered as inputs into the web-based ANN application to obtain predicted FoS values for each bench. Each bench's parameters were entered separately, and the corresponding predicted FoS was recorded from the application output. The application processed the inputs instantaneously through the trained 5-50-50-1 ANN model and returned the predicted FoS values. The percentage deviation of the application-predicted FoS from the LEM-derived FoS was then determined for each bench to assess predictive accuracy under real mine conditions.

4.2.4 RESULTS

The application-derived FoS values are compared with the LEM-derived FoS values (using Bishop's method), and the corresponding absolute and percentage errors for the three Mine II dump benches are calculated. These details are presented in Table 3.

Table -3: LEM-derived (Bishop's Method) and Application-derived slope FoS values of Mine II showing corresponding absolute and percentage errors [4].

Slope (Bench)	FoS by LEM (Bishop's Method)	FoS by ANN model (using application)	Absolute error	Percentage error	Slope category
1-1' (A)	1.187	1.162	0.025	2.11%	Moderately stable
2-2' (B)	1.200	1.189	0.011	0.92%	Moderately stable
3-3' (C)	1.923	1.987	0.064	3.33%	Highly stable

The ANN application yields FoS predictions that are in close agreement with the LEM-derived values for all three benches. The percentage errors are within acceptable limits (< 5%) across the full range of FoS values encountered, spanning from moderately stable to highly stable conditions. Critically, the model correctly classified all three benches: Benches A and B were predicted as moderately stable, and Bench C as highly stable, fully consistent with the LEM-derived results.

This demonstrates that the application can reliably indicate whether a bench slope falls within the moderately stable or highly stable regime without requiring a full LEM simulation. The deviations observed are consistent with the model's overall testing performance (RMSE = 0.054, R^2 = 0.981) and are well within acceptable bounds for a preliminary screening tool. These results confirm that the trained ANN model can be used as a rapid, field-deployable FoS estimation tool.

5. CONCLUSIONS

Through testing and real mine-based validation of the proposed ANN model as described in sections 4.1 and 4.2, the following conclusions can be drawn:

(1) The proposed ANN model demonstrates excellent predictive accuracy within the range of input parameters. The testing RMSE achieved is 0.054 with an R2 value of 0.981. This demonstrates good agreement between the predicted FoS values and those derived using the LEM.
(2) The trained model was field-validated using geotechnical and slope geometry data from a real opencast lignite mine case study [4]. The application-derived factor of safety values showed close agreement with LEM-derived reference values, with percentage errors varying between 0.92% and 3.33% as compared to the LEM-derived values, thereby confirming the model's reliability for practical field-based use.

DECLARATIONS

Competing Interests: The author declares that there are no competing interests.
Funding: No funding was received for conducting this study.
Permission: Permission has been obtained from NLC India Ltd. for publication of this article.
Data Availability: The datasets used for the current study are available in the Mendeley Data repository and can be accessed at https://doi.org/10.17632/6fcg43nvrm.1
Author Contributions: Conceptualization, Methodology, Formal analysis and investigation, Writing - original draft preparation, Writing - review and editing: Syed Saarim Ahmad (corresponding author).

REFERENCES

1) Paul M.M., Varma M., Salini U, "Analysis of slope stability using SLOPE/W software", Indian Geotechnical Conference IGC 2022 15th – 17th December, 2022, Kochi, India.

2) Khajehzadeh M, Keawsawasvong S, "Predicting slope safety using an optimized machine learning model Heliyon", 2023 Nov 29;9(12):e23012. doi: 10.1016/j.heliyon.2023.e23012.

3) Kinsley H., Kukiela D, "Neural networks from scratch in python", https://nnfs.io/.

4) Ahmad, S.S, "Slope stability analysis of opencast mine dump using the limit equilibrium method—a case study", Mining, Metallurgy & Exploration, 41, 2555-2566. https://doi.org/10.1007/s42461-024-01081-4.

5) Burman, A. & Acharya, S. & Sahay, Rajeev & Maity, Damodar, "A comparative study of slope stability analysis using traditional limit equilibrium method and finite element method", Asian Journal of Civil Engineering. 16. 467-492.

6) Chatterjee, J. & Amini, Farshad & Cooley, L., "A comparative slope stability analysis of New Orleans I-wall subjected to hurricane loading", International Journal of Geotechnical Engineering. 3. 444-453. 10.3328/IJGE.2009.03.03.445-453.

7) Rotaru, Ancuța & Bejan, Florin & Almohamad, Dalia, "Sustainable Slope Stability Analysis: A Critical Study on Methods. Sustainability" 14. 8847. 10.3390/su14148847.

8) Zhu, D. Y. "Investigation on the accuracy of the simplified Bishop method," In: Proceedings of the 10th. Internal Symposium on Landslides and Engineered Slopes, China, pp. 1055-1057.

9) Khajehzadeh M, Keawsawasvong S, "Predicting slope safety using an optimized machine learning model," Heliyon. 2023 Nov 29;9(12):e23012. doi: 10.1016/j.heliyon.2023.e23012.

10) Kenan G., Turkan K, "Assessing the factor of safety using an artificial neural network: case studies on landslides in Giresun, Turkey", Environmental Earth Sciences, 73, 8639-8646. DOI: 10.1007/s12665-015-4027-1

11) Chakraborty A., Goswami D, "Slope Stability Prediction using Artificial Neural Network (ANN)". International Journal Of Engineering And Computer Science. Vol. 6, 21845-21848, DOI: 10.18535/ijecs/v6i6.49

12) Pacci S., et al., "Artificial neural networks in soil quality prediction: Significance for sustainable tea cultivation", Science of the Total Environment. Vol. 947. https://doi.org/10.1016/j.scitotenv.2024.174447

13) Millan M.A. et al., "Application of artificial neural networks for predicting the bearing capacity of the tip of a pile embedded in a rock mass", Engineering Applications of Artificial Intelligence. Vol. 124. https://doi.org/10.1016/j.engappai.2023.106568.

14) Nejad F.P. et al., "Prediction of pile settlement using artificial neural networks based on standard penetration test data", Computers and Geotechnics. Vol. 36(7) 1125-1133. https://doi.org/10.1016/j.compgeo.2009.04.003

15) Sergey L., Christian S., "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", Vol. 1. https://doi.org/10.48550/arXiv.1502.03167.

16) Streamlit IO. A faster way to build and share data apps. https://streamlit.io/. Date accessed: 12th February, 2026.

17) Ahmad, S.S., "Slope factor of safety (FOS) predictor", https://neural-network-afmsrbuef6ehbx64buhrcg.streamlit.app/. Date accessed: 12th February, 2026.