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Deep neural network and ANN ensemble for slope stability prediction

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ABSTRACT

Purpose: Application of deep neural networks (DNN) and ensemble of ANN with bagging for estimating of factor of safety (FOS) of soil stability with a comparative performance analysis done for all techniques.

Design/methodology/approach: 1000 cases with different geotechnical and similar Geometrical properties were collected and analysed using the Limit Equilibrium based Morgenstern-Price Method with input variables as the strength parameters of the soil layers, i.e., Su (Upper Clay), Su (Lower Clay), Su (Peat), angle of internal friction (φ), Su (Embankment) with the factor of safety (FOS) as output. The evaluation and comparison of the performance of predicted models with cross-validation having ten folds were made based on correlation-coefficient (CC), Nash-Sutcliffe-model efficiency-coefficient (NSE), root-mean-square-error (RMSE), mean-absolute-error (MAE) and scattering-index (S.I.). Sensitivity analysis was conducted for the effects of input variables on FOS of soil stability based on their importance.

Findings: The results showed that these techniques have great capability and reflect that the proposed model by DNN can enhance performance of the model, surpassing ensemble in prediction. The Sensitivity analysis outcome demonstrated that Su (Lower Clay) significantly affected the factor of safety (FOS), trailed by Su (Peat).

Research limitations/implications: This paper sets sight on use of deep neural network (DNN) and ensemble of ANN with bagging for estimating of factor of safety (FOS) of soil stability. The current approach helps to understand the tangled relationship of various inputs to estimate the factor of safety of soil stability using DNN and ensemble of ANN with bagging.

Practical implications: A dependable prediction tool is provided, which suggests that model can help scientists and engineers optimise FOS of soil stability.

Originality/value: Recently, DNN and ensemble of ANN with bagging have been used in various civil engineering problems as reported by several studies and has also been observed to be outperforming the current prevalent modelling techniques. DNN can signify extremely changing and intricate high-dimensional functions in correlation to conventional neural networks. But on a detailed literature review, the application of these techniques to estimate factor of safety of soil stability has not been observed.

Keywords: Upper clay, Lower clay, Peat, Angle of internal friction, Embankment, Factor of safety, Slope stability, Deep neural network, Ensemble

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METHODOLOGY OF RESEARCH, ANALYSIS AND MODELLING

1. Introduction

There has been considerable attention to slope stability in the past few decades. Slope stability analysis is also critical in terms of instabilities occurring during the construction and design of highways, excavations, and earthen dams. Instabilities may result from various external natural factors, including hydrologic events, variations in the groundwater table, and earthquakes. A large number of slope failures taking place around the globe can lead to significant consequences, including loss of life. Slope stability can be accessed quantitatively by predicting a factor of safety which is generally used to decide whether a slope is stable. The slope stability prediction is dependent on the combined effects of geological, hydrological, and soil parameters which makes it a non-linear multivariate complex problem.

Although slope stability analysis is challenging, its existence has significantly developed in the last few decades. Hence, modelling the soil slope under different conditions becomes very important for better assessment and design to take adequate measures at the correct time. Researchers from the Geotechnical domain are constantly developing new prediction models to determine slope stability as technology advances.

Numerous studies [1-3] have developed a lot of numerical-based conventional approaches to analyse the soil slopes. Jing [4] traditionally used the limit equilibrium approach, which is based on methods of slices. The technique requires assuming the potentially critical slip surface before further calculating the factor of the slope's safety (F). Moreover, different assumptions have to be made regarding forces between two slices [5]. However, it recently demonstrated that the solutions calculated using LEMs could not be realistic enough [6].

The finite element-based method is another calculation method that is more powerful and realistic, working on the principle of the material's stress-strain curve. The slope failure surface is found automatically using this method through the zones where the shear strength of the soil is low to resist the shear stresses, which is worked upon using the strength reduction method (SRM) to analyse the slope stability and estimate the factor of safety.

Since there are multiple factors involved in modelling slope stability, empirical-based numerical models generally lack in fully representing real-life complexities and considering the critical physical characteristics such as slope geometry and geotechnical properties influencing the stability of slopes.

With the rise of modern computational power leading to data-based learning models, there has been a rapid advent in using advanced data-based techniques such as artificial intelligence (A.I.) and genetic algorism (G.A.). Although data-based learning methods have been used in other fields [7-17], various AI-based methods have been successfully applied to geotechnical assessment, too, in recent times. The complex non-linear and multidimensional relationships among the physical parameters associated with the evaluation of slope stability demonstrate different machine learning algorithms such as logistic regression, gradient boosting machine, random forest, decision tree, support vector machine, and multilayer neural network [18,19], have been recently developed.

However, among the available A.I. techniques, ANNs are the most used in soil and rock mechanics. ANNs have shown a satisfying performance in simulating the patterns and developing non-linear relationships for multivariate dynamic systems by mimicking the biological neural network. The performance can be further improved by using multiple sets of hidden layers, also known as deep neural networks.

The advanced neural network methods have been deployed for developing better relations and patterns between the geotechnical parameters to predict the safety factors of slopes reasonably with great accuracy comparable with the traditional approaches using different kinds of ANN models as discussed in the works [20-28]. ANN has proved to outperform the traditional empirical-based methods in slope stability analysis [29]. There has been a constant effort to develop and deploy more advanced A.I. methods to study slope stability in recent times by integrating different models. Gordan et al. [30] found that deploying particle swarm optimization in combination with neural networks has a higher performance capacity than ANN. A study focuses on using some evolutionary optimization techniques such the GA, ES, DE, and BBO to conduct Slope stability analysis [31]. The recent study by Bui et al. [32] illustrated using a genetic algorithm combined with the M5Rules algorithm and compares different machine learning based techniques used to calculate the Factor of Safety. Liao & Liao [33] demonstrated the use of the multivariate adaptive regression splines (MARS) for inter-relationships among input parameters and then compared it to the results of the backward propagation neural network (BPNN). A hybrid stacking ensemble approach using an artificial bee colony algorithm has been recently experimented with to enhance slope stability prediction using ANN models [34].

Various advanced studies have highlighted the applications of different machine learning (ML) approaches in the analysis of Geotechnical underground structures such as caverns [35] and the inflow models within drill and blast tunnels [36] to improve upon any limitations of the traditional approaches.

Further, the studies have demonstrated the prediction performance of such models to predict the optimized parameters during the construction life of tunnels, such as disc cutters life of TBM [37]. And present a methodology to identify risks and reduce the uncertainties involved within such constructions' cost and time estimations [38].

Finally, these advanced machine learning approaches have been implemented in the analysis and forecasting of slope stability and understanding of the influence of each parameter on the final predicted factor [39]. The latest study has also demonstrated the use of such unique statistical approaches to determine rock strength parameters [40].

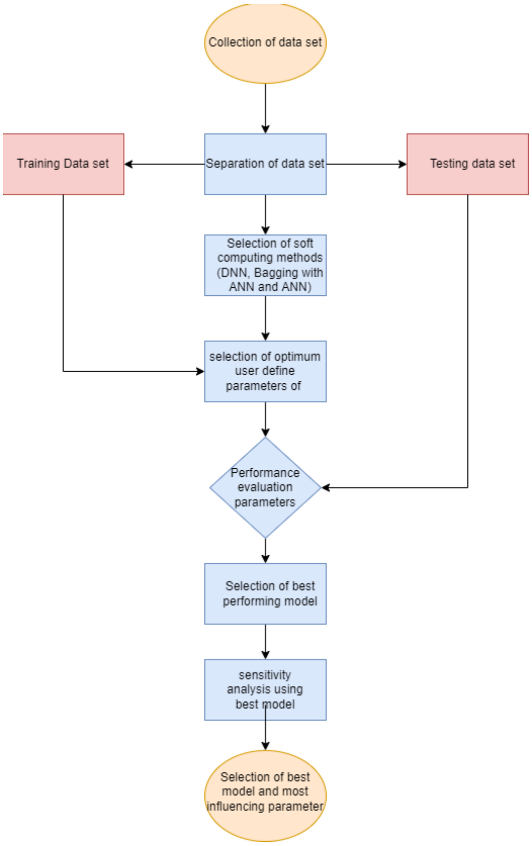

Fig. 1. Flow chart showing the structure of the article

In recent years, it has been observed that DNN has widespread and much research in various civil engineering problems, as reported by several studies. It has also been observed to outperform the current modelling techniques [41-48]. DNN is capable of signifying extremely changing and intricate high-dimensional functions in correlation to conventional neural networks [49]. The authors did not come across the application of DNN to predict the factor of safety of soil stability in previous literature. More work on the application of DNN is required, with Figure 1 showing the structure of the work done. This paper demonstrates the use of the deep neural network (DNN) and ensemble for estimating factor of safety of soil stability. The main objective of the current approach is to help understand the tangled relationship of components of soil stability with the factor of safety of soil stability using DNN and ensemble of ANN with bagging and further to compare all techniques.

2. Material and methods

2.1. Deep neural network (DNN)

A deep neural network is a complex form of neural network consisting of multiple hidden layers, hence a more advanced feature extraction algorithm. It is generally represented as an arrangement of multiple neurons in layers (like the neurons in the brain) having connections with other neurons. These neurons then transmit a message or stimuli to other neurons based on the received input forming a complex network that learns a specific response.

The processing node forms the basic element of a BPNN. The behavior of processing nodes is similar to the biological neuron performing two functions, i.e., summing up the input values and passing this sum through an activation function for computing the output. An activation function, f, can be any differentiable function. The layers of BPNN are arranged using all the processing nodes, and the interconnection of each layer is maintained with the following layer. Nodes of the same layer do not have any interconnection. The input layer in BPNN distributes the input data without performing any processing. Subsequent to this layer lie one or more processing layers, usually referred to as hidden layers, whereas the output layer is the final processing layer. This type of neural network, having two or more latent layers containing numerous nodes and utilizing advanced numerical demonstration, is generally known as a deep neural network.

Associated weight exists in all interconnections between each node. Net input (n_y) to the unit is calculated by summation of the product of the values passing from input layer through these linkages and associated weight, represented as follows:

$$n_y = \sum_x w_{yx} o_x \quad (1)$$

where unit x denotes the input unit, the weights of the linkage to unit y from unit x and o_x the output of the unit x. This is followed by the activation function for transforming the net input attained by the aforementioned equation to yield an output (o_y) for the unit y.

Conventionally, two widely used non-linear activation functions, namely the sigmoid and hyperbolic tangent, are used in combination with BPNN. For detailed learning of the intricacies of data, non-linearity is introduced in the neural network using activation functions. Saturation and sensitivity are two significant problems observed with changes around the mid-point of sigmoid and hyperbolic tangent functions [50].

The activation function, mainly the rectified linear activation function (RELU), can be considered a piecewise linear function and a significant algorithmic change in the design of DNN [50] in the last decade.

In deep learning, RELU is the ubiquitously used activation function that yields the input value as output, provided it is positive; otherwise, the output is zero. The best feature of this activation function is simplicity in its training and ability to surpass other activation functions with DNN. The RELU function is calculated as:

$$f\left(n_j\right) = max\left(0, n_j\right) \quad (2)$$

Initializing BPNN using correct weights within a reasonable range is crucial for the neural networks to function properly. It can be obtained by random weight initialization but performs poorly. So, another technique for weights initialization for DNN was proposed, known as the Xavier weight initialization [51].

Another important user-defined parameter is the learning rate. Mostly, it is set randomly between 0 and 1. Adaptive gradient descent, which used an adaptive learning rate procedure, was used with DNN [50]. Adaptive moment prediction based on the optimal algorithm was used for updating network weights during training. Adam calculates separate learning rates for diverse parameters and requires the setting of various user-defined parameters so default values of all user-defined parameters as delineated were used and were found to work fine with data in this study [52]. Overfitting may be observed in DNN due to the overfitting problem because of limited training data, thus giving a poor performance with test data. Regularization methods are used to prevent the overfitting problem improving the performance of DNN models on more extensive data [50].

The learning algorithm is slightly modified through regularization techniques, enabling better model generalisation. Srivastava et al. [53] proposed the introduction of the dropout layer in DNN’s design to enhance the generalization capability of the model and avoid the overfitting problem.

Dropout is a regularization technique used for refining the performance of a DNN model. This method employs the random removal of a node, in a latent or a manifest layer, along with all incoming and outgoing connections, which is done through random weights setting these nodes to zero. Probability *p* (representing the possibility of keeping the node during training, ranging between 0 and 1) is assigned to an individual node. Excluding the choice of the activation function, the probability of retention is essential in the dropout layer in the hidden layers, which are defined generally by the user and can be optimized through a trial-and-error process.

A set of various user-defined parameters like the number of nodes in each hidden layer, optimization algorithm, number and the type of hidden layers, the weight initialization method, learning rate optimization algorithm, the batch size (number of training samples in one iteration), number of epochs (one epoch is defined as passing the entire training dataset through the neural network in both forward and backward direction) and the type of activation function for the output and hidden layers are essential requirements of deep neural network and are selected using multiple random iterations. To implement DNN, WEKA 3.9.5 was used in this study.

2.2. Artificial neural network (ANN)

A neural network works similarly to the brain, consisting of a connection of neurons by finding patterns from the input data it is fed on. A neural network generally consists of three layers consisting of the input, output, and hidden layers, as shown in Figure 2. The neurons of the input layer receive some input from an external environment. Without performing any computations, this layer sends the inputs to the hidden layer, which then performs the computations and provides the predicted outputs to the output layer. The output layer consists of single/multiple neurons that transmit the system's output.

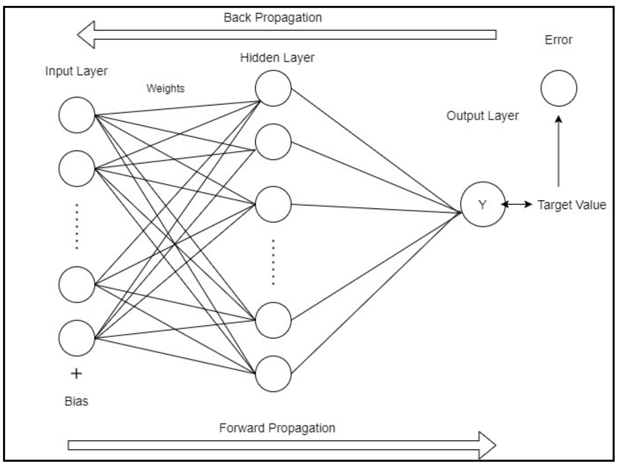

Fig. 2. Single hidden layer neural network

The neural network is a two-way process; the first process is about training the model. It finds a suitable non-linear relationship by generating suitable weights between the different variables and then processing the sum using a suitable non-linear transfer function to produce a prediction. The network then learns by adjusting its weights between the different neurons in response to the residuals between the predicted output values and the target output values. It runs a backward process to update the weights until the error has been minimized. The neural network is fed a different data set in the next testing phase. In this phase, the neural network, as predicted using the trained weights from the previous phase, is, compared to the target output values. This is done to check whether the ANN overfits/under fits a certain amount of data.

A low bias and low variance are significant for an ANN model and can be further improved by ensemble learning. An ensemble learning method is a technique that can combine the predictions from different machine learning models to make more precise predictions than any individual model would be able to make.

2.3. Bagging

Bagging created by bootstrap aggregating the ANN model is one of the earliest methods proposed by Breiman [54] to reduce the prediction error of learning machines. It is an effective regularization technique that is used to minimize variance from the training data set and improve the model's accuracy by using multiple copies of it trained on different subsets of data from the initial training dataset. It helps to avoid overfitting on certain data and can improve the stability and performance of the ANN models.

3. Criteria for evaluating model performance

The performance of various techniques for the prediction of the factor of safety of soil stability has been estimated using various performance evaluation parameters, including the coefficient of correlation (CC), Nash-Sutcliffe model efficiency coefficient, root mean square error (RMSE), mean square error (MSE) and scattering index (S.I.), the expressions for which are mentioned in Table 1.

The degree of linear dependence between the observed value and the predicted value [55] is quantified using the correlation coefficient CC, with its value close to zero means no association between observed and estimated observations, although when it approaches one signifies a perfect fit amongst the observed and estimated observations [56]. But the model's accuracy cannot be evaluated using CC alone, so additional indicators such as R2, RMSE, MAE, SI, and NS can be used to assess the models' appropriateness. Broadly, the higher value of CC and the lower value of RMSE, MAE, SI and NS lead to a decrease in errors among the observed and estimated value, thereby specifying the correctness of models.

Table 1.
Performance indicators

Performance indicator	Expression
Correlation coefficient	$CC = \frac{\sum_{i=1}^{N}(A_i-\bar{A})(P_i-\bar{P})}{\sqrt{\sum_{i=1}^{N}(A_i-\bar{A})^2}\sqrt{\sum_{i=1}^{N}(P_i-\bar{P})}}$
Nash-Sutcliffe model efficiency coefficient	$NS = 1 - \left[\frac{\sum_{i=1}^{N}(A_i-P_i)^2}{\sum_{i=1}^{N}(\bar{A}-\bar{P})^2}\right]$
Root mean square error	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i-A_i)^2}$
Mean absolute error	$MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert P_i - A_i\rvert$
Scattering index	$R^2 = \frac{RMSE}{\bar{A}}$

where:
A = actual or observed values, P = predicted values,
$\bar{A}$ = mean of actual values, N = number of observations

4. Dataset

This research focuses on applying various models, such as Artificial Neural networks, their ensemble, and Deep Neural networks in the slope stability assessment prediction. It compares the predicted results using different models to the actual safety factors. A geotechnical investigation was conducted near and across the earthen embankment location using field tests and lab tests on collected samples to derive the geotechnical strength properties for the different soil layers for developing a dataset for the model. The various tests were conducted on only specific scattered locations leading to an uncertainty in the derived parameters caused by natural spatial variation, measurement uncertainty, etc. Hence, the statistical distribution of the geotechnical parameters was calculated using all the collected data for different scattered points. The statistical distribution for the geotechnical parameters has been then used to generate Monte Carlo simulations leading to various possible combinations of the strength parameters keeping the geometry and the unit weights as constant quantities. In this study, the LEM-based Rocscience Slide2 has been used to conduct the stability analysis utilizing its in-built numerical code to identify the most probable critical slip surface after generating multiple trial slip surfaces. The height of the embankment, the slope angle, and the total unit weights of the different soil layers have been assumed to have constant values. The undrained strength parameters (Su) and the friction angle (Φ) have been used as dependent stochastic variables for the different soil layers in the study.

4.1. Preparation of dataset

The LEM conducts stability analysis based on a set of geotechnical properties and the geometry of the given embankment/slope section by simulating the various Conditions. The dataset has been generated using the Monte Carlo Simulations for the normal statistical distributions of different geotechnical parameters, as given in Table 2. A total of 1000 unique data pairs have been generated and used to conduct the stability analysis using the LEM-based Morgenstern-Price method in Rocscience Slide2 by simulating the earthen embankment to generate safety factors. The labelled dataset has been then used for the preparation of the model and tested on the same data using the WEKA software's inbuilt cross-validation with a 10-fold approach. Different soft computing techniques such as multilayer perceptron, multilayer perceptron with bagging and deep neural networks have been performed, and the performance of the different soft computing techniques has been compared.

4.2. Model development

Development of the ANN model and ANN with bagging requires selecting specific optimal user-defined parameters to get the best prediction of the factor of safety. This is to get the best prediction of the factor of safety which is carried out using the interactive trial and error processes until optimal values of goodness fit parameters are obtained. To find the optimal set of user-defined parameters, a large number of iterations were carried out. This was done by keeping a single parameter constant while varying the values for other parameters in each trial until the highest correlation coefficient value was obtained for that specific parameter. This step was repeated for all the different user-defined parameters. In the case of the artificial neural network (ANN), Different user-defined parameters such as the learning rate (α) and the momentum (m) have been working, whereas in the case of ANN with bagging, the parameter number of bagging iterations was chosen to be optimized to get the highest value of correlation coefficient (CC).

Preparation of the DNN model includes choosing the parameters like the number of hidden layers, dropout layers, p, activation function, epochs, batch size, instance iterator, type of weight initiation, and updater.

At the start of the design process, the model is trained and developed considering a couple of chief parameters. On assessing the model's outcomes, if found not a sufficient number of primary parameters are increased, successively. Model accuracy is evaluated by comparing the model's outcomes with the actual data.

In DNN and ensemble of ANN with bagging, performance and accuracy of the model are validated by various performance indicators such as coefficient of correlation (CC), Nash-Sutcliffe model efficiency coefficient (N.S.), root mean square error (RSME), mean absolute error (MAE) and scattering index (S.I.) to depict the correlation between output and input parameters. In a nutshell, input parameters consist of five units processed to an output node of the factor of soil stability safety. In modeling, the results contain the actual value and predicted value of the factor of soil stability and error. It also contains network validation through coefficients CC, RSME, MAE, SI and NS obtained.

Table 2.
Statistical distribution of input parameters and safety factor

Material Type	Su (Upper Clay)	Su (Embankment)	Su (Lower Clay)	Φ (Sand)	Su (Peat)	Factor of safety
Min-Max	2.79-66.98	6.14-79.02	5.15-54.94	5.00-65.42	4.67-56.62	0.63-3.03
Mean, kPa	35.2	42.5	30.3	34.6	32.06	1.87
Standard deviation, kPa	10.4	12.5	8.6	10.5	9.05	0.37
Kurtosis	-0.0205	-0.1191	-0.3120	-0.3387	-0.0701	0.1618
Skewness	0.0290	-0.0847	0.0144	-0.0016	-0.06371	-0.1093

5. Results and discussion

5.1. ANN and ANN with bagging

Development of ANN requires selecting the optimal user-defined parameters, which were optimized using a large number of trial iterations. The ANN was chosen to best work at a Learning rate (α) of 0.1 and a momentum (m) of 0.3 with the number of iterations as 2000. In the case of ANN with bagging, the number of bagging iterations was 20.

Figures 3 and 4 below illustrate the cross-validation results comparing the predicted and the observed safety factors (Fs). The goodness of fit parameters has also been calculated as listed in Table 3, which clearly illustrates that ANN with the bagging booster works better than the ANN model without bagging. Figures 3 and 4 conclude that ANN and ANN with bagging can give reasonable predictions for the factors of safety.

5.2. DNN

Development of the DNN model requires selecting the optimal number of hidden layers and defining the number of neurons in those hidden layers having a suitable activation function at the respective nodes. Three hidden layers containing 80, 60, and 40 neurons were selected to obtain the best fit with the observed data.

The DNN model was optimized in a user-defined parameters algorithm used with three hidden layers (80, 60, 40 nodes), epochs =20, batch size=100, instance iterator = 5, and activation function ReLU. The above values were obtained after optimizing the model based on performance indicators after many trials. Figure 5 illustrates the cross-validation result comparing the predicted and the observed safety factors (Fs) using DNN. The study outcomes show that the DNN model gives a better correlation coefficient than ANN and its ensemble. Also, other fitness parameters

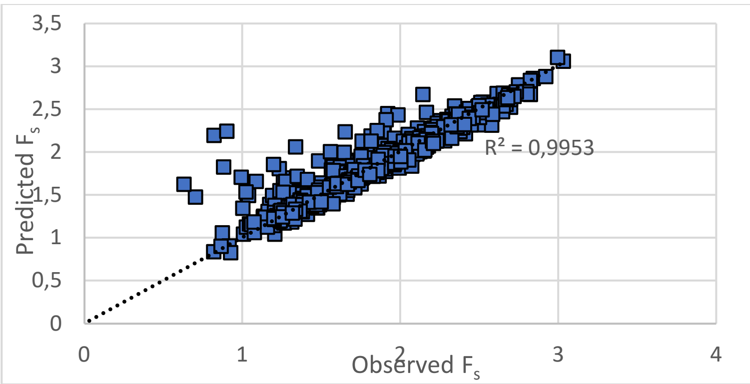

Fig. 3. Scatter plot of observed and predicted output by ANN

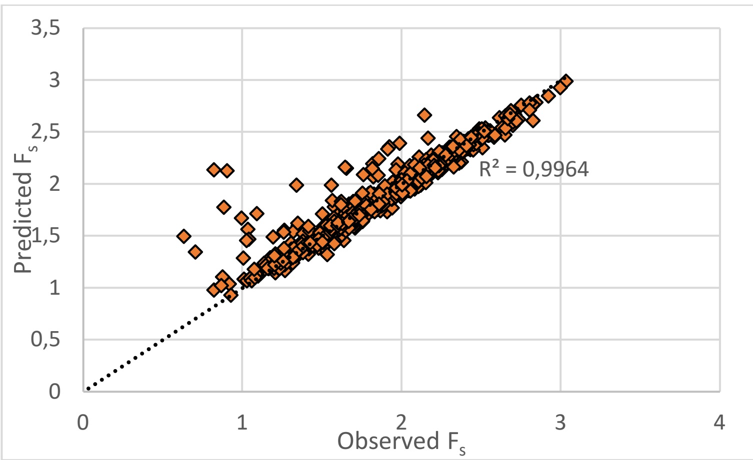

Fig. 4. Scatter plot of observed and predicted output by ANN with bagging

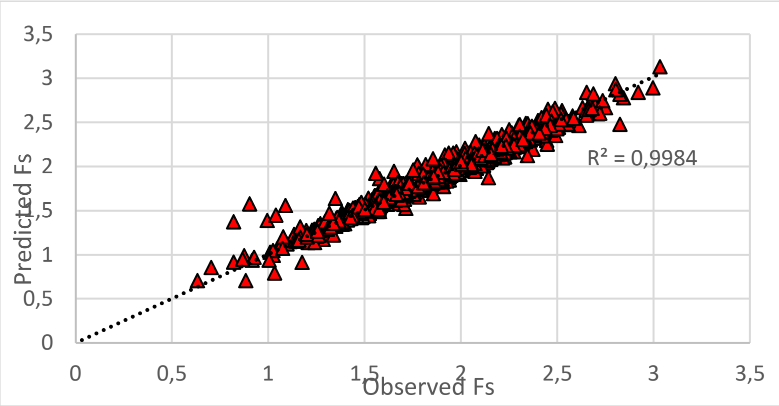

Fig. 5. Scatter plot of observed and predicted output by DNN

Table 3.
Sensitivity analysis using DNN model

Input Combinations	Input parameter removed	ANN	
		CC	RMSE
Su (Upper Clay), Su (Lower Clay), Su (Peat), Φ(sand), Su (Embankment)	None	0.9779	0.078
Su (Upper Clay), Su (Lower Clay), Su (Peat), Φ(sand)	Su(Embankment)	0.9033	0.1587
Su (Lower Clay), Su (Peat), Φ (sand), Su (Embankment)	Su(Upper Clay)	0.91	0.156
Su (Upper Clay), Su (Peat), Φ(sand), Su (Embankment)	Su(Lower Clay)	0.6232	0.2874
Su (Upper Clay), Su (Lower Clay), Φ (sand), Su (Embankment)	Su(Peat)	0.7988	0.2215
Su (Upper Clay), Su (Lower Clay), Su (Peat), Su (Embankment)	Φ(sand)	0.9636	0.0981

Table 4.
Performance evaluation parameters for different computing models

Approach	CC	MAE	RMSE	SI	NS
ANN	0.9346	0.069	0.1316	0.0701	0.8713
ANN with Bagging	0.9508	0.0567	0.114	0.0608	0.9035
DNN	0.9779	0.0524	0.078	0.0416	0.9548

Table 5.
Optimal value of user-defined parameters of DNN and Ensemble

Algorithm	Parameters (User defined)
Deep Neural Network	Three hidden layers (80, 60 and 40 nodes), three dropout layers with p=0.5, epochs =20, batch size=100, instance iterator =5, Activation function ReLU, Weight initiation =XAVIER, Updater= ADAM.
ANN	Learning rate (α)= 0.1 Momentum (m) = 0.3 Iterations= 2000.
ANN with bagging	Bagging iterations = 20.

for DNN are better than ANN and its ensemble. The observed versus predicted graphs for DNN emphasize the DNN predictive power.

5.3. Comparison of models

Different machine learning and deep learning-based computation techniques have been used to predict factors of safety in the present study. The performance evaluation parameters for the same have been listed in Table 4 for the cross-validation of 10 folds with the optimal value of user-defined parameters of DNN and ensemble given in Table 5. The safety factors as predicted using all the different computation models have been compared to the observed safety factor in Figure 6, which illustrates the optimization of the model as taking place during the cross-validation stage with the increase in the data set iterations.

5.4. Sensitivity analysis

A sensitivity analysis for the DNN model was conducted to illustrate the sensitivity of the predicted results on the dependent input parameters used for predicting the factor of safety. Each of the different input parameters, such as Su (Upper Clay), Su (Lower Clay), Su (Peat), Φ(sand), Su (Embankment), has a peculiar effect on the output Factor of safety. The different input combinations provided in Table 3 were considered by removing a single dependent variable in each case. And its effect on predicted F.S. was hence estimated using the root mean square error (RMSE) and coefficient of correlation (CC) being the primary performance criteria in the case of the developed DNN model. As shown in Table 3, the Su (Lower Clay) has the highest influence in predicting the factor of safety compared to other input parameters, which have little influence over the prediction capability of DNN models.

6. Conclusions

Although neural networks have the advantages of:

i) storing information on the entire network,
ii) the ability to work with incomplete knowledge,
iii) the ability to make machine learning, and
iv) parallel processing capability, higher predictive accuracy is observed in ensembles.

Test results improvement is observed with the size of the ensemble. Reduction in generalization error of the prediction is the motivation for using ensemble models. With the use of the ensemble approach, the model's prediction error reduces as long as the base models are diverse and independent. Most practical data mining solutions utilize ensemble modelling techniques. Bagging or bootstrap aggregating is an ensemble modelling algorithm trained with data subsets randomly selected from the training dataset to boost model variance. An artificial neural network contains two or more hidden layers between input and output layers with a set of weighted inputs and output using an activation function or algorithm. Deep learning is nothing but an ANN with multiple hidden layers, and it is responsible for the rapid development that's going on in the Machine Learning industry right now. In such a neural network, deep learning contains many hidden layers (usually 150). Increase in the amount of data results in an increase in the performance of deep learning algorithms. The study investigated the usage of advanced A.I. data-based models to conduct multi-variate analysis of slope stability (as shown in Figs. 7-9).

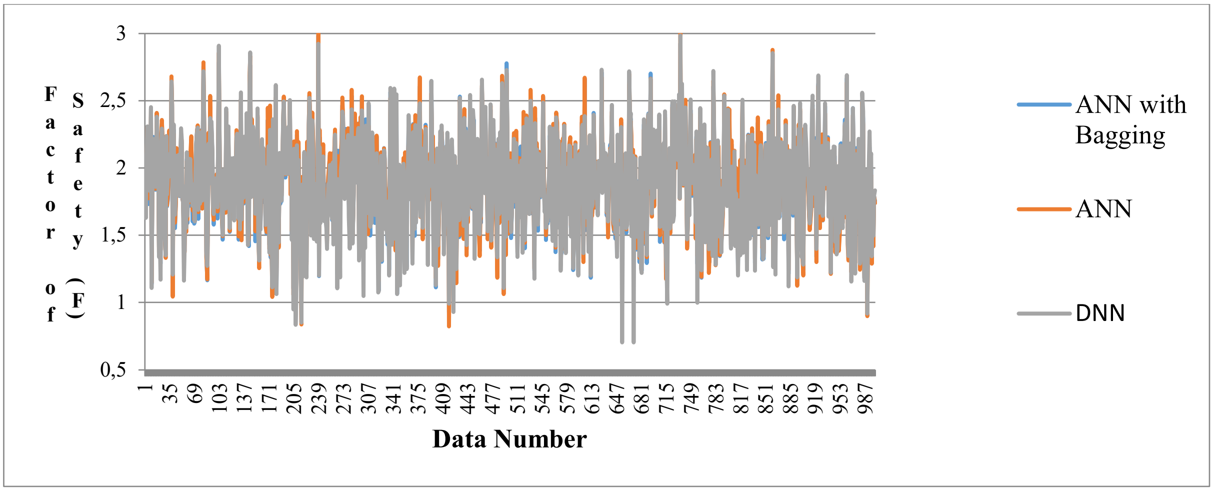

Fig. 6. Performance of various modelling techniques

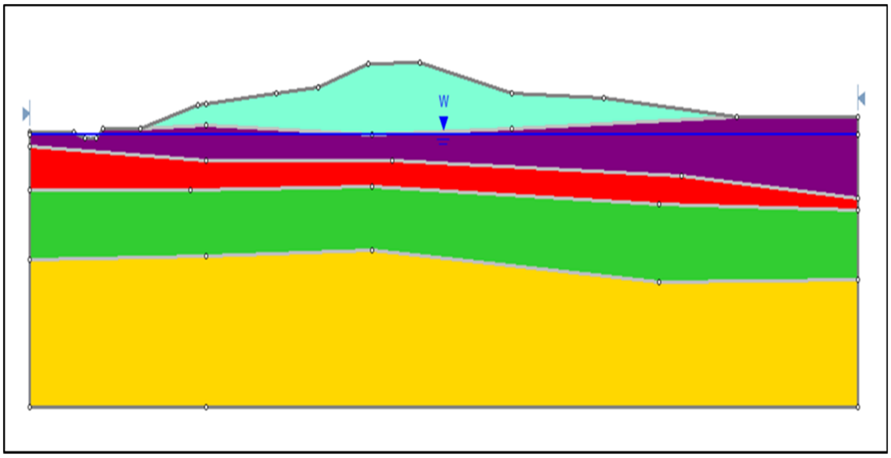

Fig. 7. Considered embankment with five subsoil layers

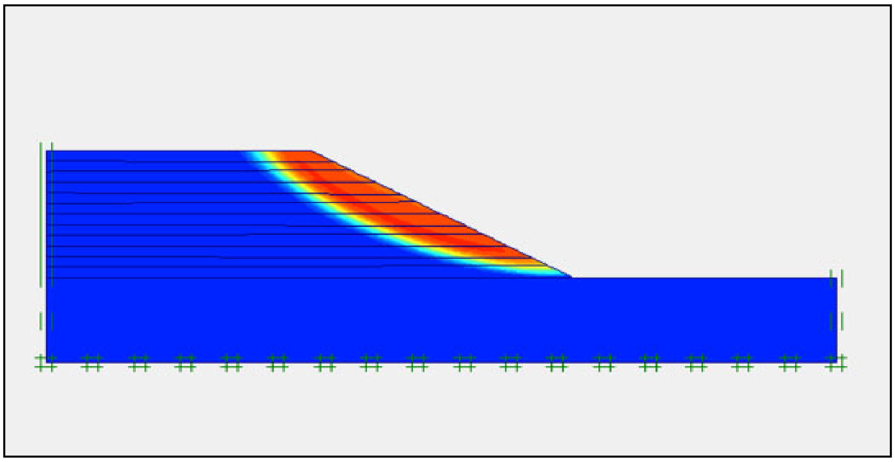

Fig. 8. Slope stability analysis

Fig. 9. Real slope failure

This was done to compare their accuracy against the traditional empirical numerical methods of conducting soil slope stability analysis to predict the factor of safety. there is a complex association between the input parameters and the factor of safety of soil stability which can be easily visualized and understood by Artificial Intelligence Techniques. To realize the association between the input and output parameters and the impact of input parameters on the factor of safety of soil stability, models were created using three techniques, i.e., DNN, ANN, and ensemble of ANN with bagging. The study explored the potential of DNN, ANN, and ensemble of ANN model by contrasting their outcomes for estimating the factor of safety of soil stability. The significant inference from this study is the outperformance of the DNN model over ANN and its ensemble with bagging on all performance indicators. Therefore, it can be used for estimating the factor of safety of soil stability accurately with specified inputs. The results showed that these techniques have the remarkable capability and possibility for estimating the factor of safety of soil stability. Sensitivity results reveal that the Su (Lower Clay) is the utmost significant factor when the DNN model is implemented to estimate the factor of safety of soil stability and is the most pertinent parameter in the approximation of the factor of safety of soil stability for this data set. This artificial intelligence technique can be timesaving, cost and labour required for performing experiments. Thus, these approaches can boast and accelerate the rate of technological advancements in geotechnical engineering.

An artificial neural network is still developing, thereby necessitating awareness of the assumptions underlying the techniques and its limitations by potential users of this new tool (i.e., neural network technique).

Further study regarding ANN should involve collecting more field data that can be used to enhance training and evaluation of the model. Also, the effect of pore water pressure in a more comprehensive manner, including the time-dependent nature of pore pressure and slope failure, can be considered.

Future research can also take the principal component analysis and ranking of input factors to develop the neural network model.

It can potentially conduct a probabilistic analysis of slope stability efficiently, wherein multiple simulations of Slope stability can be performed using the ANN approach saving loads of time and computational power.

Further, the results motivate the development of similar models within other applied fields of geotechnical analysis, such as the Random field approach, Soil displacements, pore water analysis, and foundation design.

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