International Journal of GEOMATE, March., 2023, Vol.24, Issue 103, pp.42-51
ISSN: 2186-2982 (P), 2186-2990 (O), Japan, DOI: https://doi.org/10.21660/2023.103.3532
Geotechnique, Construction Materials and Environment

COMPARATIVE ASSESSMENT OF VARIOUS ARTIFICIAL NEURAL NETWORK TECHNIQUES FOR ESTIMATING THE SAFETY FACTOR OF ROAD EMBANKMENTS

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*Corresponding Author, Received: 26 July 2022, Revised: 02 Jan. 2023, Accepted: 10 Feb. 2023

ABSTRACT: The slope-stability analysis is one of the most important parameters for ensuring a safe design of road embankments. Currently, various traditional approaches to computing this variable can be seen in the literature. Among them, the finite element method is considered an accurate way to define the safety factor of road embankments. Previous research has investigated the capability of artificial neural networks for rapid safety-factor estimation to overcome the long process of modeling and calculations required in the aforementioned approach. However, most of these studies have focused on a single type of neural network and did not investigate the capabilities of other approaches. Therefore, this study is intended to evaluate the performance of various artificial neural network techniques in predicting the safety factor of road embankments. Within this context, the feed-forward back-propagation, cascade forward neural networks, and general regression neural network results will be compared and benchmarked against various methods used to predict this parameter. Moreover, it is intended to report the influence of neural network architecture on the accuracy of the estimation. Generally, the study results have shown that an artificial neural network provides a rapid and accurate method for calculating road embankments' safety factors. Besides, the best neural network model achieved a coefficient of determination of about 0.91 and a root mean square error of 0.236, which proves the efficiency of this technique. Moreover, the reliability assessment by comparing the neural network models against the traditional methods has shown that they provide better agreement with the finite element technique.

Keywords: Artificial neural networks, Safety-factor, Road embankments, Feedforward back-propagation, cascade forward neural networks, General regression neural network

1. INTRODUCTION

One of the significant natural catastrophes is landslides which frequently occur on cut slopes alongside roadways in mountainous locations. Different incidents are documented every year in populated areas resulting in consequences to human life, harm to the existing road network, property loss, and urban growth [1]. In addition, the durability of road-cut highway slopes is crucial since even minor mistakes might result in severe financial losses and even human deaths [2]. An upward or downward inclined surface with a higher end or side than the other is called a slope [3]. The evaluation of slope stability safety factors is a routine procedure that begins by computing the factor of safety for a particular sliding surface using the technique of slices, then identifying the "crucial" surface associated with the least factor of safety connected with many potential sliding surfaces [4]. Nowadays, limit equilibrium, finite element, finite difference, discrete element, and soft computing approaches are used to determine the safety factor of natural and artificial slopes [5, 6].

Nowadays, an artificial neural network (ANN) is considered an efficient method for developing accurate estimation models for the rapid design and assessment of structural systems [7]. Over the last few decades, this approach has been applied extensively in the engineering field to solve numerical problems by constructing a model that maps the input and output of a given dataset [8]. Previously, ANN was used in various civil engineering problems, such as concrete mixtures' mechanical properties prediction [9, 10, 11, 12], damage detection [13, 14, 15], structural response estimation [16, 17, 18], soil behavior modeling [19, 20, 21]. On the other hand, multiple models using the feed-forward back-propagation neural network technique were developed for slope stability evaluation [22, 23, 24, 25, 26]. Das et al. [27] proposed a differential evolution neural network model for estimating slope safety factors. Girdab et al. [6] adopted a combination of particle swarm optimization and neural network to evaluate the seismic slope stability. Chakraborty and Goswami [28] and Erzin and Cetin [29] compared the performance of multiple linear regression to the feed-forward back-propagation neural network technique in predicting slope stability. Generally, their finds have shown that the ANN approach provides better results compared to the regression one. Therefore, it can be noticed that most of the studies available in the literature that focused on predicting the safety factor of road embankment slopes were limited to using a single type ANN network known as feed-forward back-propagation and did not good into details on the efficacy of other neural network architectures. Accordingly, this study is intended to investigate the accuracy of various types of ANN in estimating the safety factor of road embankments. Feed-forward back-propagation, cascade-forward neural network, and generalized regression neural network models will be developed and optimized within the study context. Thereafter, the efficiency of each ANN architecture will be highlighted and benchmarked against the five of the most commonly used conventional methods, including the finite element approach.

2. RESEARCH SIGNIFICANCE

The present study aims to evaluate the effectiveness of different artificial neural network (ANN) architectures in predicting the safety factor of road embankments. The primary significance of this research lies in the identification of the most accurate ANN model among the examined configurations, as well as in the comparison of the ANN performance with that of traditional methods. The outcomes of this investigation have the potential to contribute to the advancement of the current state of the art in the field of road embankment stability assessment, as well as to the practical application of ANNs for this purpose.

3. MATERIALS AND METHODS

3.1 Research Methodology

Indeed, the safety factor of slopes is a critical parameter for designing road embankments [30]. Accordingly, accurate and rapid prediction of this variable is essential for expediting the procedure for designing such a structure. Nowadays, the finite element approach is considered a reliable method to accurately find the safety factor in slopes [31]. Nevertheless, this method requires a long process of modeling and computing to define the safety factor of slopes. Accordingly, this study suggests using ANN models to estimate this parameter rapidly. Indeed, previous studies have mainly focused on adopting the feed-forward back-propagation neural network architecture for slope stability estimation [32, 33, 34].

In contrast, the performance of other architectures in such prediction tasks is still unclear. Thus, this study investigates the capabilities of three different neural network models known as feed-forward back-propagation, cascade-forward neural network, and generalized regression neural network for predicting the safety factor or road embankment. Once the models are developed and optimized, their results will be compared to the traditional approaches.

3.2 Utilized Database

The data obtained for this research were from an open-source repository [35]. The dataset that will be in this study used for training and testing the ANN models were collected from comprehensive parametric research on various road embankments' safety factors computed using the finite element approach. These synthetic cases included various heights such as 6 m, 12 m, 18 m, and up to 24 m. Table 1 shows the dataset's descriptive statistics. The database generally comprises a wide range of slope heights and angles as well as soil properties. Accordingly, the reliability of the conclusions driven from this study is ensured based on the range of data used and its sample size.

3.3 Artificial Neural Network

The artificial neural network (ANN) is an arithmetical network method based on interconnected processing elements called neurons that function in parallel to provide a result based on the defined aim. ANN was developed to digitally mimic aspects of the human brain's working neural network composed of billions of linked neurons with the ability to transmit signals to nearby neurons. In addition, ANN typically modifies strategies depending on a specific philosophy to predict the resolution of complicated challenges affected by various circumstances [36, 37].

The typical ANN architecture consists of three main components: the input layer, which contains a group of neurons used to store input data, the output layer, and the hidden layer, which, as its name indicates, cannot be viewed directly. The hidden layer consists of neurons that aid ANN in recognizing complex corrections between different inputs and outputs by adding nonlinearity to the network processing architecture. Finally, the output layer is the last step where all outcomes will be stored [37].

Furthermore, various forms of neural networks, including RBF networks, multi-layer perceptron, and recurrent networks, are categorized into neural networks depending on how input moves through the network layers and, ultimately, how each network computes. The domain of the problem must determine the type of ANN that should be used. The most frequent applications of the ANN system are used in classification and regression problems. Moreover, designing an ANN model requires careful consideration of the quantity of transfer function technique, hidden layers, and hidden neurons [38].

Table 1 Descriptive statistics of the adopted database

Input/Output of ANN	Variable	Sample Size	Mean	Standard Error of the Mean	Standard Deviation	Variance	Coefficient of Variation	Sum of Squares	Minimum	Q1	Median	Q3	Maximum	Skewness
Input	Height of Slope Embankments	288	12.75	0.373	6.331	40.08	49.65	58320	6	6	12	18	24	0.39
	Slope Angle	288	58.46	0.358	6.073	36.88	10.39	994802	45	56.31	59.87	63.44	63.44	-1.11
	CBR	288	7.667	0.31	5.258	27.65	68.59	24864	3	3	5	15	15	0.63
	Specific Weight	288	21	0.088	1.489	2.216	7.09	127644	18	20	20.75	22.75	23	-0.15
	Moisture Content	288	13.25	0.233	3.962	15.7	29.9	55068	7	9.25	13.5	17.25	20	0.12
	Deformation Modulus	288	30	0.703	11.92	142.2	39.74	300000	10	20	30	40	50	0
	Cohesion	288	10	0.635	10.78	116.2	107.8	62160	2	4	6	9.5	40	1.93
	Friction Angle	288	33.75	0.273	4.629	21.43	13.72	334200	25	30	35	38.75	40	-0.12
	Poisson's Ratio	288	0.275	0.001	0.025	6E-04	9.11	21.96	0.25	0.25	0.275	0.3	0.3	0
	Dilatancy Angle	288	5.063	0.041	0.694	0.482	13.72	7519.5	3.75	4.5	5.25	5.813	6	-0.12
Output	Factor of Safety	288	2.304	0.031	0.526	0.277	22.84	1608.2	0.92	1.991	2.352	2.713	3.665	-0.44

The goal of this study is to establish an appropriate setting for evaluating the capacities of feed-forward back-propagation (FFBP), generalized regression neural network (GRNN), and cascade forward neural network (CFNN) for precisely recognizing and forecasting pulse-like earthquakes. Seventy percent of the total datasets were chosen at random to train the ANN, and the remaining thirty percent were split into two groups of fifteen percent each for testing and validation. Additionally, a hidden layer ANN was created as an initial model for each ANN technique required. Through trial and error, different numbers of neurons were evaluated, and finally, inaccurate discrepancies were discovered. The same procedure was repeated for each hidden layer until a tiny error was identified; the performance of each ANN model was evaluated using multiple error analysis techniques. A common ANN model for the industrial sector is feed-forward back-propagation, as shown in Fig. 1. This training method involves changing the connection weights and biases. The typical process for determining output results from a collection of input data using hidden layers is multiplying each input value by its corresponding weights and adding a bias to this summing. Additionally, a nonlinearity function (activation function) modifies the result and distributes it to the next layer (output layer).

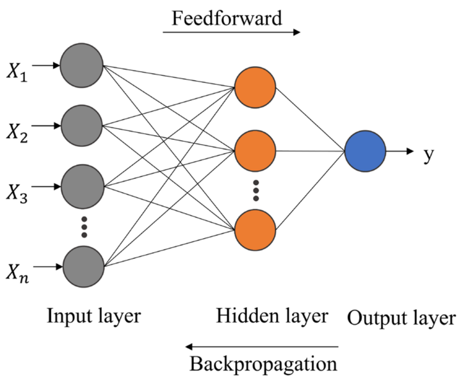

Fig.1 Representation of general architecture of the FFBP network

Figure 2 represents a cascade-forward neural network (CFNN) that is close to FFBP. The input layer coincides with the predicted input data, and then the weights are adjusted for each deep learning model. The previous results are linked to the input results, and the weights are adjusted adequately after comparing the input layer values with the values of the hidden nodes [39]. The CFNN provides extremely accurate and efficient outputs for most scenarios. Therefore, the results obtained from CFNN networks are significantly more precise than those obtained from FFBP networks, Since the CFNN structure integrates the input layer and output layers. Furthermore, the additional connections may accelerate the network's learning targeted correlation [40, 41].

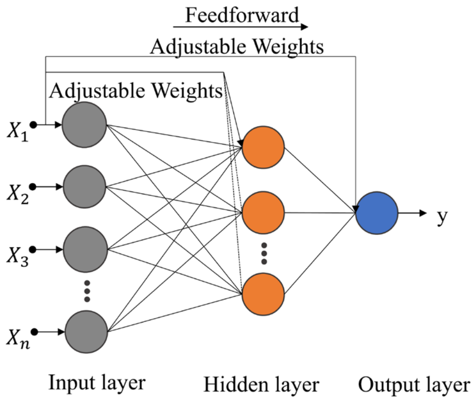

Fig.2 Schematic diagram of general architecture utilized in CFNN

The illustration in Figure 3 is the input, summation, pattern, and output layer of the generalized regression neural networks (GRNN). The fundamental difference between the GRNN and both the FFBP and CFNN is the network's design since the GRNN consists of four layers. Each specific operating parameter is set for every node in the input layer and is linked to the second pattern layer. Therefore, each unit presents a different training pattern. The output measures the variation for the input and recorded patterns in the learning pattern. S takes the sum of outputs, and D calculates the unadjusted outputs of the pattern layer. Therefore, each pattern neuron in the pattern layer will be coupled with both S and D synapses in the summing layer [42]. As a result of the summing and output layers, the output set pattern neurons are normalized.

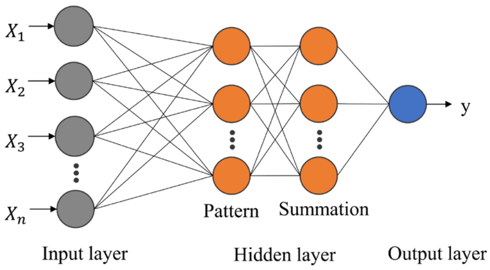

Fig.3 An illustration of the architecture applied in the GRNN algorithm

3.4 Model Development Strategy

Figure 4 outlines the method used in this study to develop the neural network models. Initially, the data is divided into testing (30%) and training (70%). Then, a series of hyperparameters (neural network parameters) is defined for each neural network model. Once the models are developed and their parameters are tuned, numerous metrics are utilized to analyze the technique's accuracy and benchmark it against the code-based method.

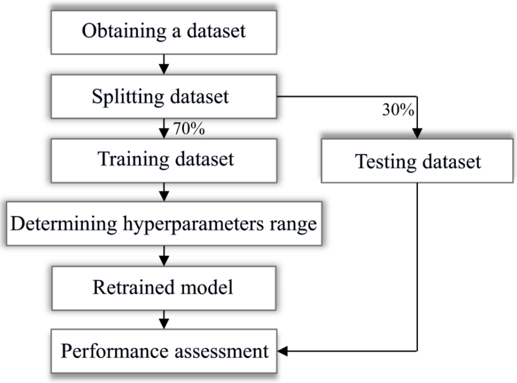

Fig.4 Illustration of the approach used for optimizing the neural network models

3.5 Performance Assessment of the Models

The performance of the ANN models will be investigated by the goodness-of-fit coefficient of determination, Eq. 1, and the error performance through the root mean square error (RMSE), Eq. 2, and mean absolute error (MAE), Eq. 3.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x}_i)^2} \quad (1)$$

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2\right]^{1/2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \bar{y}_i| \quad (3)$$

where x_i is the measured value, $\bar{x}_i$ is the average of the measured values, y_i is the estimated value, $\bar{y}_i$ is the average of the predicted values, n is the number of observations.

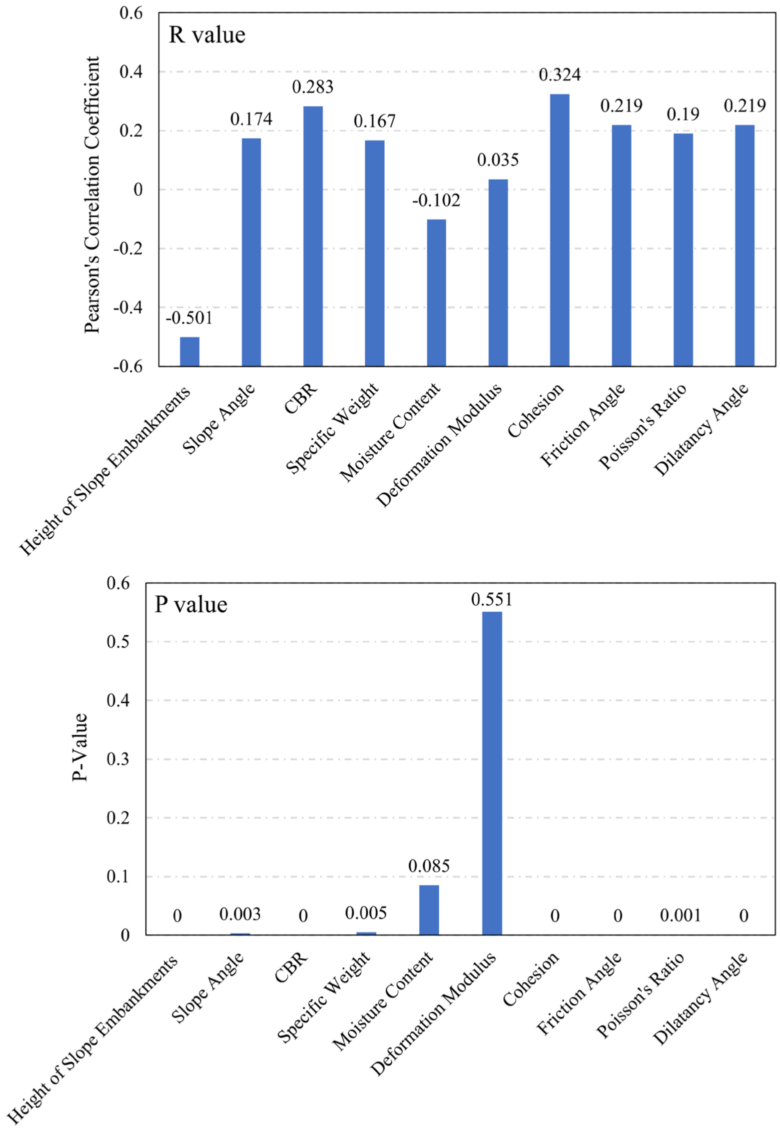

Fig.5 Significance of the various parameters on the slope safety factor

4. RESULTS AND DISCUSSIONS

As previously stated, ANN models predict the road embankment safety variables, and this research assesses the various ANN models. Thus, as illustrated in Figures 5, the impact of every given parameter in the ANN model on the slope safety factors was examined.

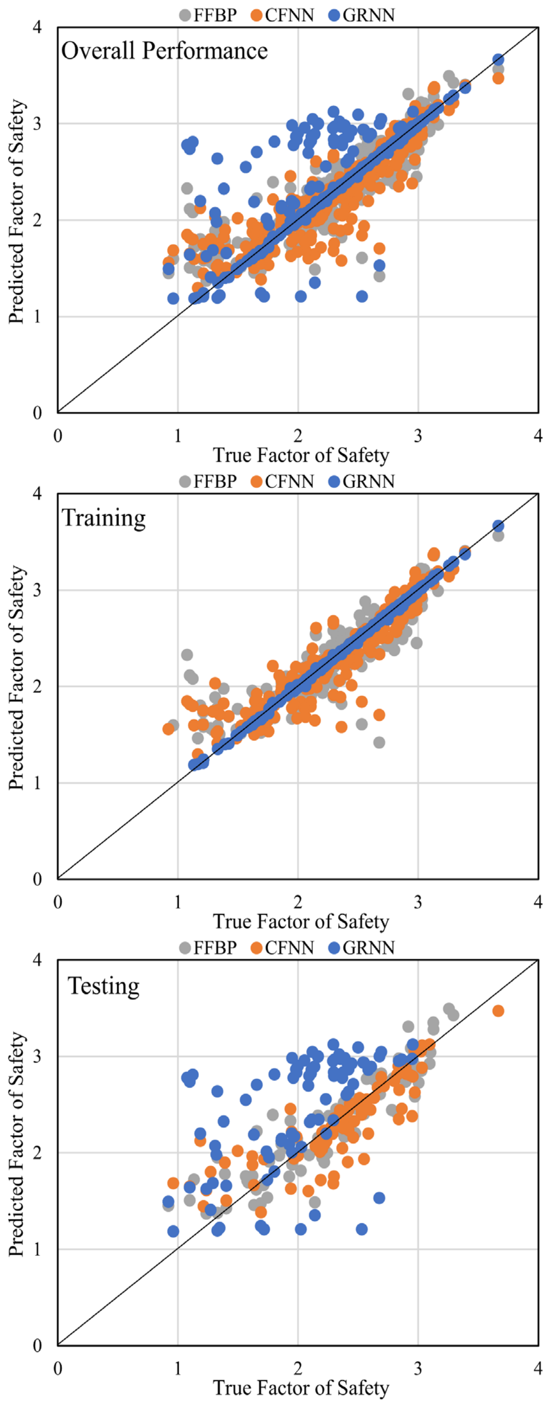

Fig.6 Results of the investigated artificial neural network models

The elevation of the road embankments has the strongest correlation, as observed in this case (Pearson's correlation coefficient). Other strong relations include soil cohesion, CBR, friction angle, and dilatancy angle. In contrast, the weakest correlation with the safety factor was obtained for the deformation modulus. Similar results to Pearson's correlation coefficient can be shown for the case of the statistical significance (P-Value).

In fact, the training, testing, and overall results of the neural network models are compared in Figure 6, and their corresponding residuals with respect to the finite element method are shown in Figure 7. It can be seen that the performance of the CFNN model was slightly better than that of the FFBP. Moreover, the results of the FFBP and CFNN models are considerably better than that of the GRNN approach for the testing dataset.

On the other hand, the GRNN showed significantly higher accuracy than the other model in the case of the training dataset. This fluctuation in the model's performance can be attributed to the GRNN model's overfitting issues. Similar trends can be observed in the statistical visualization of the safety factor, as shown in Figure 8. The goodness-of-fit and error values of the developed models are given in Table 2 for each dataset. In general, the CFNN achieved the highest overall R^2 value compared to the FFBP ad GRNN. Moreover, the overall RMSE value of the CFNN was 3.7% and 49.2% lower than that of the FFBP and GRNN models, respectively. Nevertheless, the MAE of the GRNN model was the best among others, even though the R^2 and RMSE values revealed a worse performance. These results can be attributed to the weakness of the MAE metric in detecting the overfitting issues compared to the other cases.

On the other hand, the results for the training and testing datasets in the FFBP and CFNN were similar, reflecting that these models can prevent the overfitting of the data. On the other hand, the R^2 value is below 0.9 for most cases; however, for the best one, in the case of testing the model, it was 0.912, which proves that the model has a good fitting rate. Also, the reported error is very low compared to the average safety factor, as the MAE is about 0.18 for the testing case of the best model, and the average safety factor is 2.304, which means that the error is less than 8%.

Finally, a comparison between the ANN models against five of the most used approaches for computing the safety factor of road embankments is shown in Figure 9. Indeed, these models are all benchmarked against the finite element method since it provides the most reliable source of accuracy. It can be seen that the FFBP and CFNN achieved the best matching with the finite element ones, especially for the range of data between the first quartile and third quartile.

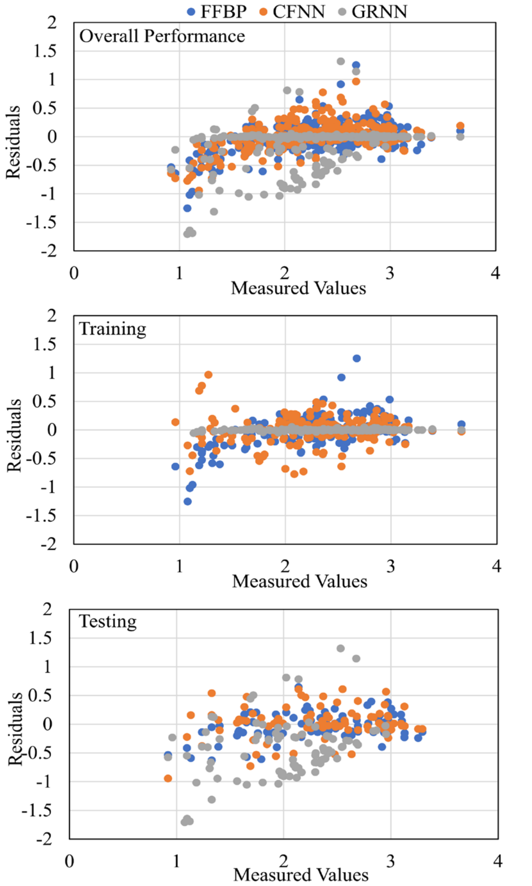

Fig.7 Residuals of the investigated models with respect to the finite element-based safety factor

In contrast, even though the GRNN technique achieved a significantly good matching with the finite element method, its results suffer overfitting problems, as stated above, and thus are unreliable. On the other hand, models such as the Fellenius and Janbu have the highest deviation from that of the finite element methods. Moreover, FFBP and CFNN models were better than the Bishop and Morgensten-Price methods. Therefore, it can be concluded that a well-trained CFNN (since it had better overall performance compared to the FFBP) model can replace traditional alternatives by means of reaching an accuracy close to the finite element method while still offering a considerably rapid estimation of the safety factor compared to using the finite element method.

Table 2 A comparison between the performances of the optimized models

Performance		R^2	RMSE	MAE
All	FFBP	0.874	0.255	0.177
	CFNN	0.883	0.246	0.166
	GRNN	0.782	0.367	0.169
Training	FFBP	0.854	0.263	0.175
	CFNN	0.899	0.228	0.152
	GRNN	1.000	0.013	0.007
Testing	FFBP	0.912	0.236	0.180
	CFNN	0.848	0.284	0.200
	GRNN	0.554	0.672	0.550

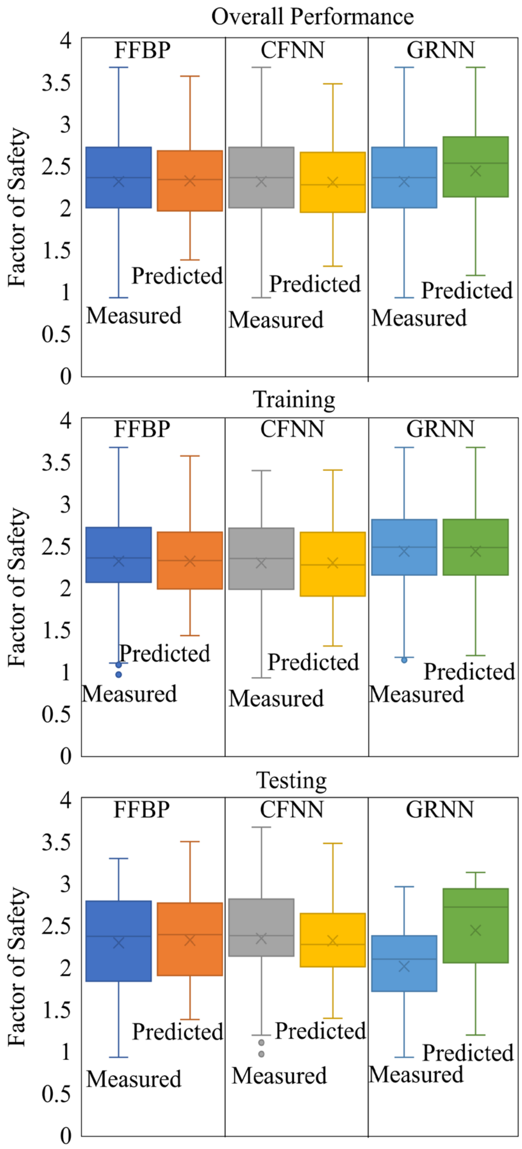

Fig.8 Comparison between statistical distributions of the investigated models

5. CONCLUSION

In conclusion, this research rapidly assesses the capability to predict road embankment safety variables using various ANN algorithms. Hence, the results were compared against finite element methodology, in this case, three of the most used neural network methods. In general, the results demonstrate that the FFBP and CFNN models outperform the GRNN model in terms of accuracy. Furthermore, the GRNN does not infer high-reliability results, and it was discovered that the FFBP and CFNN deliver dependable findings. Although previous studies have mainly adopted the FFBP method for predicting the safety factor of slopes, this study shows that the GFNN method achieves better overall goodness-of-fit and error metrics than the FFBP.

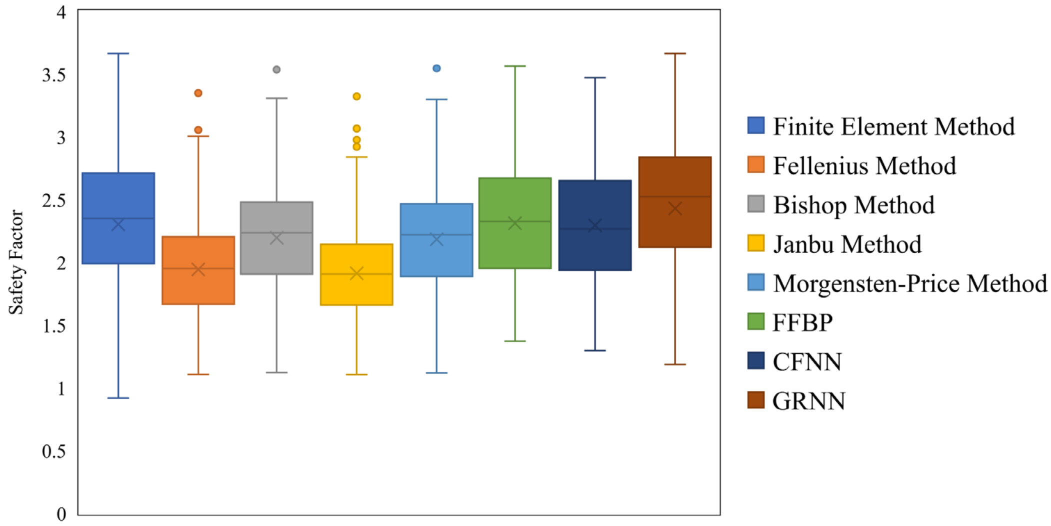

Fig.9 Benchmarking and statistical distribution of ANN results against five of the most commonly used conventional methods

On the other hand, it was shown from the comparison with traditional models that the FFBP and GFNN have the best matching with the finite element outcomes compared to very commonly used techniques such as Fellenius and Bishop methods. This means that the ANN technique shows a suitable and high accurate alternative to the finite element method when rapid estimation is needed.

6. REFERENCES

[1] Kanan M., and Kumar A., "Slope stability analysis and design their control measures," International Journal of Engineering Research and Technology, 2019, pp. 2278-0181.

[2] Kainthola A., Verma D., Thareja, R., and Singh, T. N., "A review on numerical slope stability analysis," International Journal of Science, Engineering and Technology Research, vol. 2, no. 6, 2013, pp. 1315-1320.

[3] Salunkhe D. P., Bartakke R. N., Chvan G., and Kothavale P. R., "An overview on methods for slope stability analysis," International Journal of Engineering Research and Technology, vol. 6, no. 3, 2017, pp. 2278-0181.

[4] Chen Z. Y., and Shao C. M., "Evaluation of minimum factor of safety in slope stability analysis," Canadian geotechnical journal, vol. 25, no. 4, 1988, pp. 735-748.

[5] Donald I. B., and Chen Z., "Slope stability analysis by the upper bound approach: fundamentals and methods," Canadian Geotechnical Journal, vol. 34, no. 6, 1997, pp. 853-862.

[6] Gordan B., Jahed Armaghani D., Hajihassani M., and Monjezi M., "Prediction of seismic slope stability through combination of particle swarm optimization and neural network," Engineering with Computers, vol. 32, no. 1, 2016, pp. 85-97.

[7] Manzoor B., Othman I., Durdyev S., Ismail S., and Wahab M. H., "Influence of artificial intelligence in Civil engineering toward sustainable development—a systematic literature review," Applied System Innovation, vol. 4, no. 3, 2021, pp. 52.

[8] Habib A., and Yildirim U., "Developing a physics-informed and physics-penalized neural network model for preliminary design of multi-stage friction pendulum bearings," Engineering Applications of Artificial Intelligence, vol. 113, 2022, pp. 104953.

[9] Prasad B. R., Eskandari H., and Reddy B. V., "Prediction of compressive strength of SCC and HPC with high volume fly ash using ANN," Construction and Building Materials, vol. 23, no. 1, 2009, pp. 117-128.

[10] Xi X., Yin Z., Yang S., and Li C. Q., "Using artificial neural network to predict the fracture properties of the interfacial transition zone of concrete at the meso-scale," Engineering Fracture Mechanics, vol. 242, 2021, pp. 107488.

[11] Xue J., Shao J. F., and Burlion N., "Estimation of constituent properties of concrete materials with an artificial neural network based method," Cement and Concrete Research, pp. 106614, 150.

[12] Abellán García J., Fernandez Gomez J., and Torres Castellanos N., "Properties prediction of environmentally friendly ultra-high-performance concrete using artificial neural networks," European Journal of Environmental and Civil Engineering, vol. 26, no. 6, 2022, pp.

2319-2343.
[13] Bakhary N., Hao H., and Deeks A. J., "Damage detection using artificial neural network with consideration of uncertainties," Engineering Structures, vol. 29, no. 11, 2007, pp. 2806-2815.
[14] Movsessian A., Cava D. G., and Tcherniak D., "An artificial neural network methodology for damage detection: Demonstration on an operating wind turbine blade," Mechanical Systems and Signal Processing, vol. 159, 2021, pp. 107766.
[15] Tran-Ngoc H., Khatir S., Ho-Khac H., De Roeck G., Bui-Tien T., and Wahab M. A., "Efficient Artificial neural networks based on a hybrid metaheuristic optimization algorithm for damage detection in laminated composite structures," Composite Structures, vol. 262, 2021, pp. 113339.
[16] Chakraverty S., Gupta P., and Sharma S., "Neural network-based simulation for response identification of two-storey shear building subject to earthquake motion," Neural Computing and Applications, vol. 19, no. 3, 2010, pp. 367-375.
[17] Nguyen H. D., Dao N. D., and Shin M., "Prediction of seismic drift responses of planar steel moment frames using artificial neural network and extreme gradient boosting," Engineering Structures, vol. 242, 2021, pp. 112518.
[18] Yuan X., Chen G., Jiao P., Li L., Han J., and Zhang H., "A neural network-based multivariate seismic classifier for simultaneous post-earthquake fragility estimation and damage classification," Engineering Structures, vol. 255, 2022, pp. 113918.
[19] Ghani S., Kumari S., Jaiswal S., and Sawant V. A. "Comparative and parametric study of AI-based models for risk assessment against soil liquefaction for high-intensity earthquakes." Arabian Journal of Geosciences, 2022, pp. 1-18.
[20] Marrapu B. M., Kukunuri A., and Jakka R. S. "Improvement in Prediction of Slope Stability & Relative Importance Factors Using ANN." Geotechnical and Geological Engineering, vol. 39, 2021, pp. 5879-5894.
[21] Pektas A. O., and Erdik T. "Peak discharge prediction due to embankment dam break by using sensitivity analysis based ANN," KSCE Journal of Civil Engineering, vol. 18, 2014, pp. 1868-1876.
[22] Sakellariou M. G., and Ferentinou M. D., "A study of slope stability prediction using neural networks," Geotechnical and Geological Engineering, vol. 23, no. 4, 2005, pp. 419-445.
[23] Wang H. B., Xu W. Y., and Xu R. C., "Slope stability evaluation using back propagation neural networks," Engineering Geology, vol. 80, no. 3-4, 2005, pp. 302-315.
[24] Meng J., Mattsson H., and Laue J., "Three‐dimensional slope stability predictions using artificial neural networks," International Journal for Numerical and Analytical Methods in Geomechanics, vol. 45, no. 13, 2021, pp. 1988-2000.
[25] Abdalla J. A., Attom M. F., and Hawileh R., "Prediction of minimum factor of safety against slope failure in clayey soils using artificial neural network," Environmental Earth Sciences, vol. 73, no. 9, 2015, pp. 5463-5477.
[26] Choobbasti A. J., Farrokhzad F., and Barari A., "Prediction of slope stability using artificial neural network (case study: Noabad, Mazandaran, Iran)," Arabian journal of geosciences, vol. 2, no. 4, 2009, pp. 311-319.
[27] Das S. K., Biswal R. K., Sivakugan N., and Das B., "Classification of slopes and prediction of factor of safety using differential evolution neural networks," Environmental Earth Sciences, vol. 64, no. 1, 2011, pp. 201-210.
[28] Chakraborty A., and Goswami D., "Prediction of slope stability using multiple linear regression (MLR) and artificial neural network (ANN)," Arabian Journal of Geosciences, vol. 10, no. 17, 2017, pp. 1-11.
[29] Erzin Y., and Cetin T., "The use of neural networks for the prediction of the critical factor of safety of an artificial slope subjected to earthquake forces," Scientia Iranica, vol. 19, no. 2, 2012, pp. 188-194.
[30] Jamil N. S. B. A., "Soil slope stability in road construction on soft ground," Universiti Teknologi Malaysia, 2020.
[31] Jaiswal S., and Chauhan V. B., "Influence of secondary reinforcement layers to enhance the stability of steep soil slope under earthquake loading." Arabian Journal of Geosciences, vol. 15, 2022, pp. 1-15.
[32] Kumar S., and Basudhar P. K., "A neural network model for slope stability computations," Géotechnique Letters, vol. 8, no. 2, 2018, pp. 149-154.
[33] Lu P., and Rosenbaum M. S., "Artificial neural networks and grey systems for the prediction of slope stability," Natural Hazards, vol. 30, no. 3, 2003, pp. 383-398.
[34] Chakraborty A., and Goswami D., "Slope stability prediction using artificial neural network (ANN)," International Journal of Engineering and Computer Science, vol. 6, no. 6, 2017, pp. 21845-21848.
[35] Mesa-Lavista M., Álvarez-Pérez J., Tejeda-Piusseaut E., and Lamas-Fernández F., "Safety-factor dataset for high embankments determined with different analytical methods," Data in Brief, vol. 38, 2021, pp. 107315.

[36] Cha D. F., Zhang H., and Blumenstein M., "Prediction of maximum wave-induced liquefaction in porous seabed using multi-artificial neural network model," Ocean Engineering, vol. 38, no. 7, 2011, pp. 878–88.
[37] Suryanita R., Harnedi M., Enno Y., Muhamad Z., and Hendra J., "Damage Level Prediction of Reinforced Concrete Building Based on Earthquake Time History Using Artificial Neural Network," MATEC Web of Conferences, vol. 138, 2017, pp. 1–9.
[38] Arulampalam G., and Bouzerdoum A., "A generalized feed-forward neural network architecture for classification and regression," Neural Networks, vol. 16, no. 5–6, 2003, pp. 561–568.
[39] Thatoi D., Guru P., Jena P. K., Choudhury S., and Das H. C., "Comparison of CFBP, FFBP, and RBF networks in the field of crack detection," Modelling and Simulation in Engineering, 2014.
[40] Badde D. S., Gupta A. K., and Patki V. K., "Cascade and Feed Forward Backpropagation Artificial Neural Network Models for Prediction of Compressive Strength of Ready Mix Concrete," IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE), vol. 2278–1684, 2009, pp. 1-6.
[41] Gholizadeh S., "Performance-based optimum seismic design of steel structures by a modified firefly algorithm and a new neural network," Advances in Engineering Software, vol. 81, 2015, pp. 50–65.
[42] Günaydın K., and Günaydın A., "Peak ground acceleration prediction by artificial neural networks for northwestern Turkey," Mathematical Problems in Engineering, 2008, vol. 2008.