Natural Hazards

Stability Prediction of Himalayan Residual Soil Slope using Artificial Neural Network

--Manuscript Draft--

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Abstract:	In the past decade, advances in Machine Learning (ML) techniques have resulted in developing sophisticated models that are capable of modeling extremely complex multi-factorial problems like slope stability analysis. The literature review indicates that considerable works have been done in slope stability using ML, but none of them covers the analysis of residual soil slope. The present research objectives to develop an artificial neural network (ANN) model that can be applied to evaluate the factor of safety of Shiwalik Slopes in the Himalayan Region. To achieve this, published data from numerical analysis of a residual soil slope were used to develop two ANN models (ANN1 and ANN2 utilizing eleven input parameters, and scaled-down number of parameters respectively). A four-layer, feed-forward back-propagation neural network having the optimum number of hidden neurons is developed based on trial and error method. The results derived from ANN models were compared with those achieved by numerical analysis. Additionally, numerous performance indices such as coefficient of determination (R 2), root mean square error (RMSE), variance account for (VAF), and residual error were used to evaluate the predictive performance of the developed ANN models. It was found that both the ANN models showed almost similar predictions; nevertheless, the overall performance of the ANN2 model is slightly better than the ANN1 model. It is concluded that the ANN models are reliable, valid and straightforward computational tools that can be employed for slope stability analysis during the preliminary stage of designing infrastructure projects in residual soil slope.
Response to Reviewers:	Please see the attached file

Compliance to the learned editor's and reviewer's comments for the manuscript entitled "Stability Prediction of Himalayan Residual Soil Slope using Artificial Neural Network"

Manuscript Number: NHAZ-D-20-00159

Dear Editor,

We are grateful to you and the reviewers for the constructive comments and valuable suggestions to improve the manuscript. We have revised the manuscript addressing all the comments and suggestions and resubmitting the revised manuscript for your perusal and necessary consideration in the Journal of Natural Hazards. Here is a complete rebuttal of the comments and suggestions. We look forward to the positive outcome of our hard work.

Yours sincerely,

Dr. Manoj Khandelwal
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Editor's decision and comments

Dear Dr. Khandelwal,

We have received the reports from our advisors on your manuscript, "Stability Prediction of Himalayan Residual Soil Slope using Artificial Neural Network", which you submitted to Natural Hazards.

Based on the advice received, I feel that your manuscript could be reconsidered for publication should you be prepared to incorporate major revisions. When preparing your revised manuscript, you are asked to carefully consider the reviewer comments which are attached, and submit a list of responses to the comments.

Reply: Thank you for your appreciation and offer. We have incorporated all the suggestions and corrections following the reviewer's assessment in the revised manuscript.

<u>Reviewer#1</u>

Comment 1: The present study of ML should be compared with multiple regression analysis.

Reply: We appreciate the valuable suggestion given by the reviewer. However, the manuscript is focused mainly on the Artificial Neural Network (ANN) and its application in analysing slope stability problem. Thus, the multiple regression was not used to predict the behaviour of a residual slope. Thus, the comparison of ANN results with regression analysis is not made in this manuscript and it can proceed as a separate work.

Comment 2: What is the need to take ANN2 model if one can get higher accuracy by using less number of variables?

Reply: As we know that the stability behaviour of any residual slope is a function of many geotechnical and physical parameters, the author tried to develop a model incorporating all the parameters (11parameters) used by Ray et al. (2019).

Also, it was noted that the depth of failure surface in case of residual soil slope is generally limited to the soil layer only and rarely it passed through the weathered rock layer. Thus, another ANN (8 parameters) model was made by incorporating only the residual soil and slope physical parameters, neglecting the weathered bedrock geotechnical parameters.

By depicting both the ANN models, the authors tried to depict the changes in the efficiency and prediction capability of both the models when a lesser number of input parameters were used. The lesser number of input parameters model has shown a little increase in prediction efficiency than the whole parameters model. The utility of both the models depends on the availability of observed data. If detailed observation are made, then the complete model can be used, whereas if limited observations related to the top residual soil layers are made, then the lesser number of input parameters model can be applied.

Ray A, Kumar RC, Bharati AK, Rai R, Singh T (2019) Hazard Chart for Identification of Potential Landslide Due To the Presence of Residual Soil in the Himalayas. *Indian Geotechnical Journal*:1-16 doi:https://doi.org/10.1007/s40098-019-00401-6

Comment 3: One more ANN model should be developed using only higher importance parameters which can provide higher correlation coefficient with factor of safety.

Reply: In the original manuscript, two ANN models were developed and analysed. The first model (ANN1) incorporated all the available 11 parameters used by Ray et al. (2019) and the second model (ANN2) used only 8 parameters that are associated with residual soil and slope physical parameters, ignoring the weathered bedrock geotechnical properties. This was assumed based on the numerical simulation results from Ray et al. (2019) in which all the failure surface passed from the residual soil layer while the weathered bedrock layer remains stable.

As per the recommendation, a **New ANN** model was prepared, which incorporates only the higher importance parameters based on correlation analysis performed in Table 2 of the original manuscript. The analysis of the **New ANN** model shows an improved accuracy and reduce RMSE than the previous ANN1 and ANN2 models used in the original manuscript as shown in the table below.

Table showing Performance indices of the ANN models

Model	**Data**	**R^2 (%) (more is better)**	**RMSE (less is better)**	**VAF (%) (more is better)**	**Learning Rate (more is better)**	**Momentum (less is better)**
ANN1	Training Set	99.70	0.0133	99.89	0.69	0.021
	Testing Set	89.20	0.0656	88.43		
ANN2	Training Set	99.59	0.0021	98.22	0.72	0.019
	Testing Set	93.15	0.0536	88.96		
New ANN	Training Set	99.68	0.0118	99.85	0.78	0.016
	Testing Set	95.89	0.0462	98.76		

Thus, the ANN2 model (having 8 input parameters based on the assumption that failure occurs only through the residual soil layer) in the original manuscript is replaced with the **New ANN** model (having only higher importance input parameters based on the correlation coefficient) in the revised manuscript. This **New ANN** model has been designated as ANN2 in the revised manuscript (as mentioned in line 292-299 in the revised manuscript).

Comment 4: Figure 6 show relation between the output and target FoS. Why there are three figures to show one output for each ANN models. It should be clearly defined or remove the other figures to avoid any confusion.

Reply: The three graphs for each ANN model represents the relation between the output and target FoS for training, testing and the entire data. These three cases (training, testing and entire data set) are mentioned at the top of each graph along with the coefficient of regression values.

Thus, there is no need to remove the figures. In order to make it more clear for the reader, the title of the figure has been changed from:

Fig. 1 Targeted and output FoS by ANN for training, and testing

to

Fig. 2 Targeted and output FoS for both the ANN models during training, testing and entire data set

Comment 5: The present work is on residual soil, however at many places author have used overburden material. It creates confusion, so, it would be good to use the same terminology throughout the MS.

Reply: We regret the inconsistency in our part. As per the recommendation, the term ‘overburden material’ has been replaced by residual soil to avoid any confusion.

Reviewer #2:

Comments pertaining to Geological characteristics and Geotechnical study

Comment 1: Slope dimensions are not visible in field photos. Authors may add panoramic view illustrating dimensions of slope.

Reply: As per recommendation, the slope dimensions were added to the field photograph (Fig. 1). We regret to inform you that we could not add a panoramic view of the slope since no panoramic photograph was taken for the slope during field investigation and now it is not possible to get the panoramic view photograph.

Comment 2: Tension cracks were observed during field surveys? If yes, they were considered in simulation studies/ in pre-assumption of slip surfaces?

Reply: We would like to inform that out of the four sites (Nainital, Haridwar, Dehradun, and Solan) from where field investigations were carried out, and samples were collected for laboratory tests (Ray et al. 2019), only one site (Haridwar) had few tension cracks. Rest of the sites were free from any tension cracks. Thus, during simulation, no tension cracks were assumed.

Comment 3: Kindly provide boundary conditions and model environment/initial conditions.

Reply: The following boundary conditions and model environment/initial conditions were used during simulation **(Note: This is only to inform the reviewer, and the details are given in Ray et al. (2019). If the reviewer recommends, it can be added in the revised manuscript)**

"Fixed boundary conditions (zero displacements) have been used at the base of the model, and along the lateral sides, however, the slope face and the rock–soil interface were kept free for showing strain and displacement. Two-dimensional six-noded triangular plane strain elements have been used to discretise across the selected slope profile. In this study, a uniform meshing option has been used for the soil and weathered rock layer and graded meshing for the bedrock layer. The average element size of around 0.5 m,1 m, and 5 m is

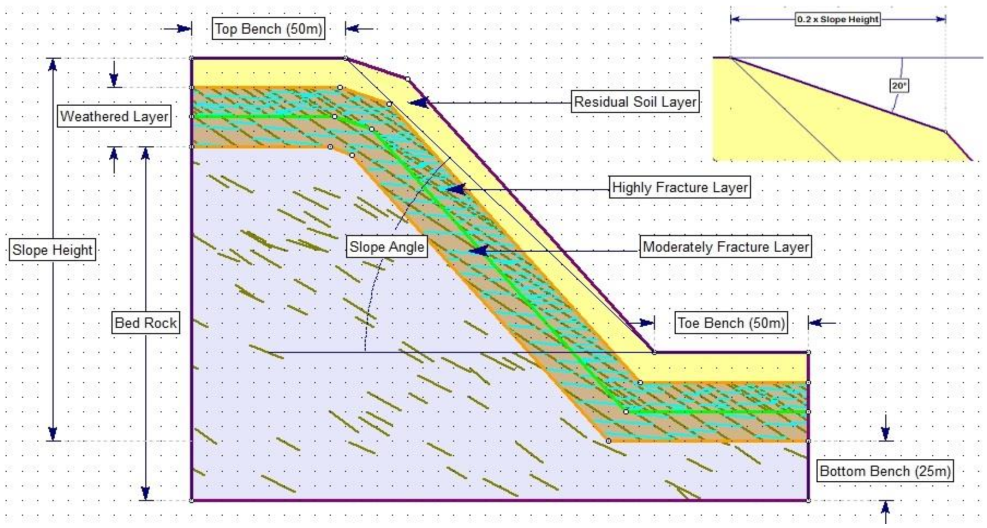
kept for the residual soil layer, the weathered rock layer, and the bedrock layer, respectively. It was assumed that no tension cracks are present on the crown of the slope. All the models evaluated under dry condition."

Ray A, Kumar RC, Bharati AK, Rai R, Singh T (2019) Hazard Chart for Identification of Potential Landslide Due To the Presence of Residual Soil in the Himalayas. *Indian Geotechnical Journal*:1-16 doi:https://doi.org/10.1007/s40098-019-00401-6

Comment 4: Residual slopes are not homogeneous in cross-section. It is also mentioned in manuscript that residual slopes have variability in mechanical and weathering characteristics. How this, variability was accounted in the geotechnical study/in simulation?

Reply: (**Note: This is only to inform the reviewer, and the detail is given in Ray et al. (2019). If the reviewer recommends, it can be added in the revised manuscript)**

We do agree with the reviewer that residual slopes are not homogenous in cross-section. Rather it depends on the intensity of weathering and generally decreases with depth as noted initially by Blight (1977). In order to incorporate the effect of weathering (heterogeneity in residual slopes) with depth, the entire slope is modelled into three layers (shown in fig below). The top layer is the residual soil layer followed by a weathered layer which overrides the bottom bedrock. The middle-weathered layer is further subdivided into two equal parts, i.e. highly weathered and moderately weathered. The top weathered layer (highly weathered) is modelled with twice the discontinuity density per unit area of the bottom weathered layer (moderately weathered). The strength parameters of the topsoil layer are obtained from large box direct shear test (Discussed in detail in Comment 8 Reviewer #2**)**. For the weathered layer, rock mass strength has been taken into account and for the bedrock, rock specimen strength has been taken into account.



Basic slope model (From Ray et al., 2019)

The detail explanation is given in:

Ray A, Kumar RC, Bharati AK, Rai R, Singh T (2019) Hazard Chart for Identification of Potential Landslide Due To the Presence of Residual Soil in the Himalayas. *Indian Geotechnical Journal*:1-16 doi:https://doi.org/10.1007/s40098-019-00401-6

Comment 5: Highlight the role of water, how it was accounted in the present study.

Reply: This study has been performed based on results obtained under dry condition. Saturation has not been considered.

Comment 6: Detailed description of litho-units is required. Instead of regional map of Himalayas, the emphasis should be towards Siwaliks only.

Reply: As per the recommendation, the following lines describing the litho-units of the Siwaliks was added in the revised manuscript (line 124-141):

"The Siwalik Group is a thick sedimentary sequence forming the youngest mountain belt of the Himalayas, and is separated from the Lesser Himalaya to the north by the Main Boundary Thrust, and the Indo-Gangetic Plain to the south by the Himalayan Frontal Thrust. The sediments of the Siwalik Group were deposited in a foreland basin of the Himalayas between the Middle Miocene and the Early Pleistocene. This foreland basin was produced by the subsequent collision of the

Indian and the Eurasian plates in Eocene time during the Himalayan orogeny. The Siwalik Group itself was divided into the Lower, the Middle and the Upper Siwalik Subgroups based on lithology and increasing grain size by Auden (1935). The Upper Siwalik Subgroup is very distinctly noticed in the form of conglomerate, sandstone, and claystone sequence in the study area. This subgroup comprises pebble and cobble conglomerates often tens of meters in thickness, with inter-beddings of sandstones and mud horizons. Middle Siwalik unit is mainly characterised with grey micaceous sandstone, siltstone with conglomerate lenses. This subgroup comprises medium to coarse-grained, micaceous, 'salt and pepper' sandstones frequently several tens of meters thick, with inter-beddings of mudstones. The Lower Siwalik Subgroup is characterised by inter-beddings of fine- to medium-grained sandstones and variegated mudstones forming a uniform cycle of about a few meters. This subgroup comprises brown, grey and purple-grey, indurated fine to coarse-grained sandstones (Kazi Tamrakar and Kumar Syangbo 2014)".

Comment 7: For large scale residual deposits, nearly flat terrain is required. Rugged topography of Himalayas do not favors large scale residual soil deposits. Discrete patches are possible in such terrain. It is suggested not to generalize residual soil slopes for entire Himalayas. Rewrite the sentence (P-4, L-108).

Reply: As per recommendation, the original line:

"Due to the harsh climatic condition of the Himalayas, continuous weathering process results in residual deposits usually composed of fine to coarse debris which covers almost the entire Shiwalik range."

<u>Has been rewritten as (line 107-111 in the revised manuscript):</u>

"Due to the harsh climatic condition of the Himalayas coupled with complex topology, geology and hydrology, the slopes are affected by weathering of varying intensity and extent. As a result, residual deposits of varying depth and spatial extent composing of fine to coarse debris are seen in the study area."

Comment 8: As mentioned in the manuscript, boulders and rock fragments were accounted in studied slopes. Since, shear strength properties in soil mass are largely controlled by clast; illustrate the size of shear box in the test. Boulders/rock fragments were accounted?

Reply: **(Note: This is only to inform the reviewer, and the detail is given in Ray et al. (2019). If the reviewer recommends, it can be added in the revised manuscript)**

Yes, we have accounted for rock fragments during shear strength analysis. A 300mm x 300mm large box direct shear equipment was used to perform the shear strength analysis. The maximum size of clast observed in the residual soil is around 135-140mm diagonally. The majority of the clast present in the soil sample is in the range of passing from 80mm and retaining at 20mm sieve. For the direct shear test, the maximum size of aggregate taken is ones passing from 80mm sieve.

To give a better idea about the residual soil composition, the sieve analysis of a sample obtained from the Dehradun, Uttarakhand site is given below.

Total weight of soil sample: 855gm

Sieve Size (mm)	Weight Retain (gm)	Cumulative Retain (gm)	% Retain	% Finer
80	0	0	0	100
20	183.725	183.725	21.4883	78.5117
4.75	104.0001	287.725	33.65205	66.34795
2	71.99998	359.725	42.0731	57.9269
0.425	262	621.725	72.71637	27.28363
0.075	168.3751	790.1	92.40936	7.590643
pan	60.89997	851		

Comment 9: Elaborate the purpose of correlation matrix provided in the manuscript. Practically no significant correlations among considered parameters. Kindly provide a brief description/one paragraph in manuscript highlighting outcomes of correlation matrix.

Reply: The correlation matrix provided in Table 2 of the original manuscript was used to identify the importance/significant parameters among the 11 input parameters affecting the FOS of a residual slope. Analysis of the correlation matrix indicates a very weak correlation between FoS and various slope stability influencing parameters except for residual soil depth and slope angle, which shows a significant positive correlation with FoS. As per the recommendation, the following lines have been added in the revised manuscript highlighting the outcomes of the correlation matrix (as mentioned in line 151-167):

"The correlation matrix obtained from the regression analysis of the slope stability influencing parameters is presented in **Error! Reference source not found.**. *Analysis of* **Error! Reference source not found.**, *deduces a very poor correlation between FoS and various slope stability influencing parameters except for residual soil depth and slope angle, making the stability analysis a very complex problem. The FoS shows a strong and a moderate negative correlation with slope angle and residual soil depth, respectively, indicating an increase in these two variable results in a significant reduction in FoS. The shear strength parameters of residual soil (cohesion and the angle of internal friction) and the angle of internal friction of weathered rock mass shows a weak positive correlation with FoS. This results in the increase in stability of residual soil slope with increase in strength parameters of residual soil and the angle of internal friction of weathered rock mass. While, the slope height, and cohesion and young's modulus of weathered rock mass shows a weak negative correlation with FoS. This can be ascertained to the fact that with an increase in slope height, the FoS decrease and with the increase in cohesion and young's modulus of the weathered rock mass, the weathered layer becomes more stable/strong with respect to the topsoil leaving the weak residual soil layer vulnerable to sliding. The young's modulus of residual soil and the strength parameter of the soil-rock joint interface (cohesion and angle of internal friction) are almost uncorrelated or having no relationship with FoS."*

This correlation matrix is used to prepare a **New ANN** model (as per the recommendation of Reviewer#1 (Comment 3)), in revised manuscript which incorporates only the higher importance/significant parameters based on correlation analysis performed in Table 2 of the original manuscript. The analysis of **New ANN** model shows an improved accuracy and reduce RMSE than the previous ANN1 and ANN2 models in the original manuscript (as mentioned in line 339-360 in the revised manuscript).

Comment 10: A database of 400 slopes was used in this study. Any typology is considered while selecting these slopes? Any similarities based on terrain or geomechanical characteristics? All are residual slopes?

Reply: **(Note: This is only to inform the reviewer, and the detail is given in Ray et al. (2019). If the reviewer recommends, it can be added in the revised manuscript)**

A convex slope profile is formulated which has been done by making the slopes at the higher level (crown portion) gentle and slopes at lower levels steeper. The entire slope is modelled into three layers (as explained along with Figure in Comment 4, Reviewer#2). The top layer is the residual soil layer followed by a weathered layer which overrides the bottom bedrock. The middle-weathered layer is subdivided into two equal parts, i.e. highly weathered and moderately weathered, to incorporate the effect of weathering with depth. All 400 models are residual soil slopes with the thickness of the residual soil layer varying from 0.5m to 15m. The overall slope angle was varied from 15^0 to 60^0, and the height of the slope was varied from 50 m to 500 m.

Ray A, Kumar RC, Bharati AK, Rai R, Singh T (2019) Hazard Chart for Identification of Potential Landslide Due To the Presence of Residual Soil in the Himalayas. *Indian Geotechnical Journal*:1-16 doi:https://doi.org/10.1007/s40098-019-00401-6

Comment 11: These slopes may be demarcated on geological map (having lithounits)

Reply: We regret to inform you that after going through literature and various website like Geological Survey of India, International Soil Reference and Information Centre (ISRIC), and European Digital Archive of Soil Maps (EuDASM) we unable to obtain the geological map (having lithounits) for the study area (Shivalik range). However, the geological maps (demarcating the sandy residual soil of the Indian Shiwalik and Nepal Shiwalik range) are available which can be included in the manuscript on the recommendation of reviewer.

Comment 12: Some typographical/grammatical errors

P-3, L40: properties. However,

P-3, L41: delete "quite distinctively"

P-5, L25: delete "has been used"

Likewise errors may be revisited.

Reply: The recommended corrections have been done in the revised manuscript.

Comments pertaining to ANN study

Comment 1: Model Evaluation: Explanation of variance account for (VAF) is missing

Reply: As per recommendation, the following explanation has been added in the revised manuscript from line 265-270:

"The function VAF which calculates the 'Variance Accounted For' between the measured and predicted values could also be used for model evaluation. The VAF is often used to verify the correctness of a model by comparing the measured values with the predicted values of the model. If VAF is 100% and RMSE is 0, the model is treated as excellent. If there is a difference between the measured and predicted values, the VAF will be lower than 100% and RMSE will be more than 0."

Comment 2: The author has mentioned in the abstract that R^2, residual error, RMSE, and variance account for (VAF) was used for model evaluation. The utility of R^2, residual error, and RMSE has been explained but the author didn't mention the utility of variance account for (VAF) for this particular problem.

Reply: as per recommendation, the following lines have been added to define the utility of variance account for (VAF) for this particular problem in the revised manuscript from line 265-270 and 351-358:

"The function VAF calculates the 'Variance Accounted For' between the measured and predicted values. The VAF is often used to verify the correctness of a model by comparing the measured values with the predicted values of the model. If VAF is 100% and RMSE is 0, the model is treated as excellent. If there is a difference between the measured and predicted values, the VAF will be lower than 100% and RMSE will be more than 0. The

performance indices obtained from the developed ANN models are presented in Table 1. The results indicate almost similar RMSE and VAF value during the training phase of ANN1 and ANN2. However, a significant difference in RMSE and VAF is observed during the testing phase. The RMSE and VAF of ANN2 during testing phase shows superior results as compared to ANN1 due to the maximum accounted variance during calculation and the use of variables having higher correlation factor which indicates the superiority of ANN2 model in predicting the outcome."

Table 1 Performance indices of the ANN models

Model	**Data**	**R^2 (%)**	**RMSE**	**VAF (%)**
ANN1	Training Set	99.92	0.0133	99.89
	Testing Set	89.20	0.0656	88.43
ANN2	Training Set	99.68	0.0118	99.85
	Testing Set	95.89	0.0462	98.76

Comment 3: Line 249-252: "After going through …… in the training set". The author must explain if 80% of the total data is separated initially for performing the subsequent training process for minimizing RMSE or every time a different set of random 80% data is used for each training process?

Reply: The following lines have been added in the revised manuscript from line 282-287:

"After going through the optimisation analysis for the present analysis, approximately 80% (320 cases) of the entire dataset was incorporated in the training set, and the remaining 20% (80 cases) was incorporated in the testing set. The training dataset was separated from the entire data, and a separate dataset consisting of these 320 data is made. During the subsequent training process, the separated dataset was used every time in order to reduce the RMSE and obtained the desire MLP."

Comment 4: Line 308: Is it variance (VAF) or variance account for (VAF)?

Reply: We regret the typo error. It has to be variance account for (VAF) and corrected in the revised manuscript.

Comment 5: How normalization of data sets were done?

Reply:

The equation for normalization is derived by initially deducting the minimum value from the variable to be normalized, then the minimum value is deducted from the maximum value and then the previous result is divided by the latter. Mathematically, Normalization equation is represented as,

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Comment 6: How did authors find optimum number of hidden layers and neurons in hidden layers?

Reply: The optimum number of hidden layer and neurons in the hidden layer is obtained through trial and error method where the objective function is to reduce the RMSE and momentum and increase the learning rate of the network as mentioned in the revised manuscript from line number 319-325 as:

"Based on the accuracy of generated results, the most suitable neural network architecture was deduced by training and testing different combinations of hidden layers and associated neurons. After going through various network combinations, the network with 11-10-10-1 architecture for ANN1 and 8-10-10-1 architecture for ANN2 is selected corresponding to minimum RMSE of 0.0133 and 0.0118, respectively. The selected ANN1 and ANN2 network has a learning rate and momentum of 0.69, 0.021 and 0.78, 0.016, respectively."

In order to understand the concept, an example is given below showing the trial and error method adopted for selection of an optimum number of hidden layers and neurons in hidden layers (**<u>Note: This is only to inform the reviewer. If the reviewer recommends, it can be added in the revised manuscript</u>**):

Model	**Network Architecture**	**Learning Rate**	**Momentum**	**RMSE Error**	
ANN1	11-10-1	0.12	0.097	0.125	
	11-20-1	0.34	0.084	0.085	

	11-10-5-1	0.52	0.047	0.021	
	11-10-10-1	**0.69**	**0.021**	**0.0133**	**Selected**
	11-15-10-1	0.67	0.026	0.018	
ANN2 (New ANN as recommended by Reviewer#1 (Comment 3)	8-10-1	0.41	0.074	0.046	
	8-15-1	0.46	0.063	0.017	
	8-10-5-1	0.59	0.047	0.0092	
	8-10-10-1	**0.78**	**0.016**	**0.0118**	**Selected**
	8-15-10-1	0.68	0.032	0.0078	

Comment 7: What training functions were used while training and testing of the network?

Reply: "Stochastic Gradient Descent" function was used during training and testing of the network (It is mentioned in Table 3 of the original manuscript).

Comment 8: General comments regarding reference

Missing some good references in the literature, please add in your list which are: -

- https://doi.org/10.1186/s40703-019-0097-3
- https://doi.org/10.1007/s11069-013-0627-9
- Kainthola et al., 2012, Finite Element Analysis of Road Cut Slopes using Hoek & Brown Failure Criterion, International Journal of Earth Sciences and Engineering 5 (5), 1100-1109
- Sarkar et. al., 2009. Stability analysis of soil slope in Luhri area, Himachal Pradesh, Mining Engineers' Journal 10 (6), 21-27

Reply: As per the suggestion of the learned reviewer, we have incorporated the references.

Stability Prediction of Himalayan Residual Soil Slope using Artificial Neural Network

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Abstract

In the past decade, advances in Machine Learning (ML) techniques have resulted in developing sophisticated models that are capable of modelling extremely complex multi-factorial problems like slope stability analysis. The literature review indicates that considerable works have been done in slope stability using ML, but none of them covers the analysis of residual soil slope. The present study aims to develop an artificial neural network (ANN) model that can be employed for evaluating the factor of safety of Shiwalik Slopes in the Himalayan Region. Data obtained from numerical analysis of a residual soil slope were used to develop two ANN models (ANN1 and ANN2 utilising eleven input parameters, and scaled-down number of parameters based on correlation coefficient respectively). A four-layer, feed-forward back-propagation neural network having the optimum number of hidden neurons is developed based on trial and error method. The results derived from ANN models were compared with those achieved from numerical analysis. Additionally, several performance indices such as coefficient of determination (R^2), root mean square error (RMSE), variance account for (VAF), and residual error were employed to evaluate the predictive performance of the developed ANN models. Both the ANN models have shown good prediction performance; however, the overall performance of the ANN2 model is better than the ANN1 model. It is concluded that the ANN models are reliable, valid and straightforward computational tools that can be employed for slope stability analysis during the preliminary stage of designing infrastructure projects in residual soil slope.

Keyword: Machine Learning; Slope Stability; Artificial Neural Network; Residual Soil.

1. INTRODUCTION

The occurrence of landslides depends on the geo-spatial and geoenvironmental characteristics of an area (Chakraborty and Goswami 2017; Pham et al. 2018; Sazid 2019; Zare et al. 2013). The Himalayan Region (HR) falls in the category of most seismically active mountain chains throughout the globe (Singh et al. 2013). Due to the prevalence of the warm-temperate and subtropical climatic condition, HR has witnessed profound and variable weathering of the bedrock (Vyshnavi et al. 2015). Residual soil is formed after complete rock weathering and disintegration (Regmi et al. 2013). Blight (1977) defines residual soil as the weathered and decomposed product of in situ rock, which has not been displaced from its original location (Fig. 1). The overall texture and composition of residual soil mimic the granulometric properties of the parent rock. It should be noted that although the residual and transported soils have many similarities, including their physical and mechanical properties, they considerably differ in strength and bonding. The heterogeneity of the residual soil profile makes the stability assessment very complex and challenging based on mere field and laboratory tests (Huat et al. 2006; Ray et al. 2019). The engineering properties can differ considerably along length and depth due to varying weathering patterns (El-Ramly et al. 2005; Little 1969).

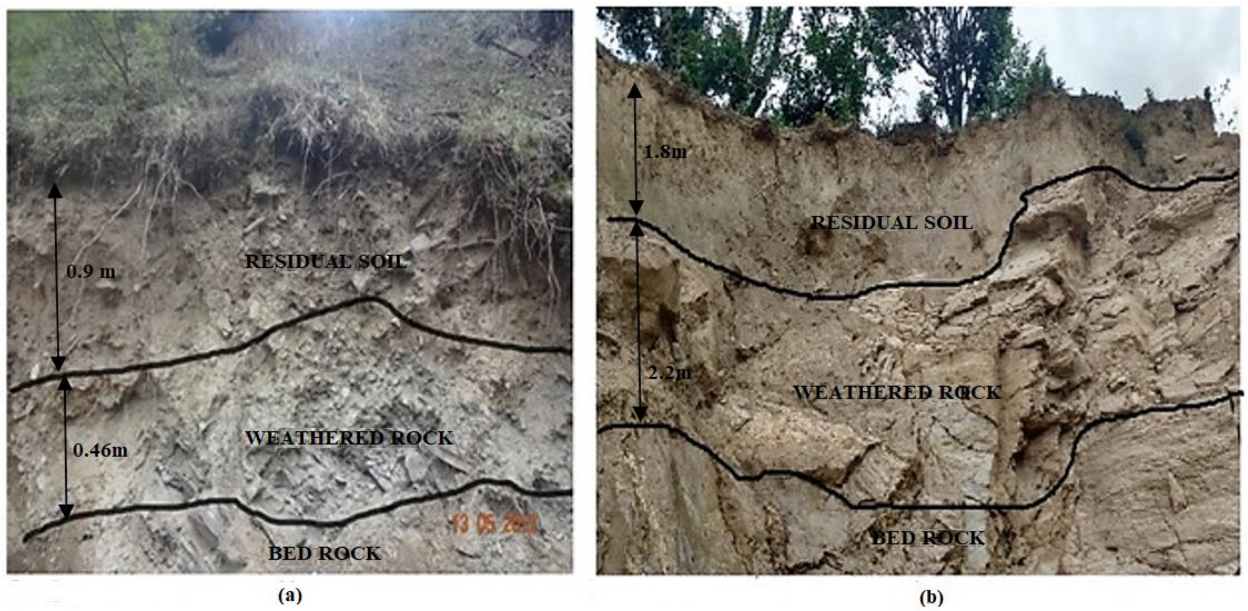


Fig. 1 Typical sub-soil profile of HR. (a) Location Parashar, Himachal Pradesh (b) Location Sonprayag, Uttarakhand

Establishing a technique toward residual soil slope stability prediction is very strenuous as a precise evaluation involves many geometric and mechanical variables (Pham et al. 2018; Qi and Tang 2018; Ray et al. 2019; Trigila et al. 2015). Such a prediction technique must have a high level of accuracy and adaptability. Furthermore, due to the demanding nature of engineering assignments, the prediction should be made in a short computational time. These requirements have aggravated the complication in evolving a precise prediction technique for slope stability analysis. In slope stability analysis, the factor of safety (FoS) is generally used to describe the overall functioning and vulnerability of a slope towards failure. The overall performance of a slope and precise prediction of its FoS is not a simple task. This is primarily due to the complexity in the precise estimation of mechanical properties of the influencing parameters, their magnitude of impact, and the intricacy of their relationships. Therefore, various sources of uncertainties govern the evaluation of slope stability (Cho 2009). The overall performance and the corresponding FoS of a slope, has been probed analytically, numerically and latest by using Artificial Intelligence (AI) by many researchers (Abdalla et al. 2015; Rukhaiyar et al. 2018). Analytical methods which include the limit equilibrium method (LEM) and the circular/non-circular failure surface method, utilises the slope displacement model for locating the possible sliding surface and the corresponding FoS. Although analytical methods are computationally efficient, due to their inherent drawbacks such as simplifications of the whole study region and utilisation of predefined failure surface, they fail to provide a complete understanding of the slope behaviour. Thus, the use of analytical methods is mostly restricted to a limited area having simple slope geometries. In order to overcome the drawbacks of analytical methods, numerical simulation was developed as a theoretically more realistic and rigorous technique for slope stability analysis (Verma et al. 2016). The major disadvantage of numerical simulation is the prolonge solution time required to set up the computer model and perform the analysis (Abdalla et al. 2015). With the development in the field of computation and data analysis, numerical simulation can now be executed within a reasonable period and higher accuracy. Other drawbacks of the numerical simulation include defining the boundary conditions that simulate the field, selection of parameters and the choice of an appropriate constitutive model which is not available in many cases (Erzin and Cetin 2013; Sakellariou and Ferentinou 2005). As a result, there is a demand for a technique with higher precision and quick response that can substitute the LEM, and numerical simulation**.** In recent years, machine learning (ML) or AI techniques have been an attractive research topic for solving geotechnical problems. Currently, AI techniques are considered to be one of the most sorted analytical techniques for instability prediction (Das et al. 2011; Khandelwal et al. 2015; Kim et al. 2018; Lu and Rosenbaum 2003; Paudel et al. 2016; Verma et al. 2016).

ML algorithms are powerful and flexible, statistical modelling tool used for formulating complex geotechnical problems, owing to their fruitful conduct in simulating non-linear multivariate problems (Chen et al. 2019; Das et al. 2011; Erzin and Cetin 2013; Kim et al. 2018; Paudel et al. 2016). One of the most commonly used ML techniques is Artificial Neutral Networks (ANN) which is comparatively new in the field of slope stability analysis. ANN techniques are proposed based on ML algorithms to learn the correlation between FoS and its influencing parameters from recorded data. Yesilnacar and Topal (2005), Pradhan and Lee (2010 b), Zare et al. (2013), Yilmaz (2010), and Pham et al. (2017) developed different ANN models to predict the stability of the slope and estimate the FoS. Previous works on AI concluded that computational intelligence tools are encouraging and should be further implemented in addressing complex geotechnical problems. It should be asserted that although the studies mentioned above are significant, there are still various problems which need to be conveyed appropriately: (1) only a limited number of physical and mechanical parameters which governs the overall stability of slopes have been used during modelling (2) slope stability analysis for residual soil has not been extensively explored.

This paper investigates the rationality of utilising AI techniques in predicting the behaviour of a residual soil slope in the HR. The objective of this paper is to develop a model based on the multivariate statistical method, such as ANN for evaluating landslide susceptibility in the study area. The results obtained from the ANN model will be validated by comparing with the results from the numerical simulation. The study area chosen for the implementation of the models is the Shiwalik Range of the Lower Himalayas.

2. SLOPE STABILITY OF HIMALAYAN RESIDUAL SOIL

Residual soil is the outcome of the rock weathering process, which is generally found under unsaturated conditions and at the same location as the parent rock (El-Ramly et al. 2002). Due to the harsh climatic condition of the Himalayan Region, coupled with complex topology, geology and hydrology, the slopes are generally affected by weathering of varying intensity and extent. As a result, residual deposits of varying depth and spatial extent composing of fine to coarse debris are seen in the study area (Fig. 1). Generally, translational and rotational slides are universal in these soils (Hungr et al. 2014; Regmi et al. 2013; Sarkar et al. 2009). Ray et al. (2019) have carried out extensive literature studies of the HR and concluded that up to moderate slope (<50^0), the thickness of residual soil varies from 2m to 10m with some places exceeding 10m before encountering the weathered bedrock. The residual soil generally comprises of medium-grained sandy soil mixed with clay, boulders and weathered rock fragments possesses a low shear strength. It can fail under various natural and anthropogenic circumstances like tectonic activities, civil infrastructure works, toe erosion by a river, and application of dynamic and dead loads. Failure generally comprises of shallow soil flow activity or creeping in the deep-seated overburden residual soil. The current study is aimed at studying the rampant slope stability problems in the Shiwalik Ranges (Sub-Himalaya) of HR (Fig. 2).

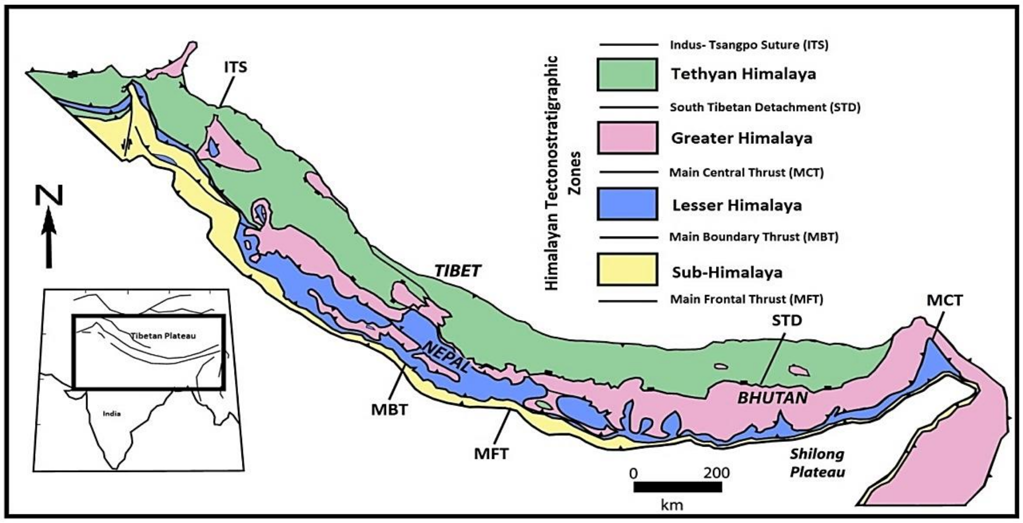


Fig. 2 Distribution of the Himalayan stratigraphic zones (McKenzie et al. 2011)

The Shiwalik Group is a thick sedimentary sequence forming the youngest mountain belt of the Himalayas. It is separated from the Lesser Himalaya to the north by the Main Boundary Thrust, and the Indo-Gangetic Plain to the south by the Himalayan Frontal Thrust. The sediments of the Shiwalik Group were deposited in a foreland basin of the Himalayas between the Middle Miocene and the Early Pleistocene. This foreland basin was produced by the subsequent collision of the Indian and the Eurasian plates in Eocene time during the Himalayan orogeny. The Shiwalik Group itself was divided into the Lower, the Middle and the Upper Shiwalik Subgroups based on lithology and increasing grain size by Auden (1935). The Upper Shiwalik Subgroup is very distinctly noticed in the form of conglomerate, sandstone, and claystone sequence in the study area. This subgroup comprises pebble and cobble conglomerates often tens of meters in thickness, with inter-beddings of sandstones and mud horizons. Middle Shiwalik unit is mainly characterised with grey micaceous sandstone, siltstone with conglomerate lenses. This subgroup comprises medium to coarse-grained, micaceous, 'salt and pepper' sandstones frequently several tens of meters thick, with inter-beddings of mudstones. The Lower Shiwalik Subgroup is characterised by inter-beddings of fine- to medium-grained sandstones and variegated mudstones forming a uniform cycle of about a few meters. This subgroup comprises brown, grey and purple-grey, indurated fine to coarse-grained sandstones (Kazi Tamrakar and Kumar Syangbo 2014).

A database of 400 slope models which were previously analysed by Ray et al. (2019), using numerical simulation technique has been used. Eleven major influencing parameters have been considered which includes young's modulus of residual soil (E_s), shear strength parameter of residual soil (cohesion (C_s) and angle of internal friction (Φ_s)), young's modulus of the weathered rock mass (E_r), shear strength parameter of the weathered rock mass (cohesion (C_r) and angle of internal friction (Φ_r)), strength parameter of the soil-rock joint interface (cohesion (C_j) and angle of internal friction (Φ_j)), average slope angle (α), slope height (H) and residual soil depth (D). The summary of the slope stability database in terms of the values of the mean, standard deviation, relative minimum, and relative maximum has been presented in Table 1.

The correlation matrix obtained from the regression analysis of the slope stability influencing parameters is presented in Table 2. Analysis of Table 2, deduces a very poor correlation between FoS and various slope stability influencing parameters except for residual soil depth and slope angle, making the stability analysis a very complex problem. The FoS shows a strong and a moderate negative correlation with slope angle and residual soil depth, respectively, indicating an increase in these two variable results in a significant reduction in FoS. The shear strength parameters of residual soil (cohesion and the angle of internal friction) and the angle of internal friction of weathered rock mass shows a weak positive correlation with FoS. This results in the increase in stability of residual soil slope with increase in strength parameters of residual soil and the angle of internal friction of weathered rock mass. While, the slope height, and cohesion and young's modulus of weathered rock mass shows a weak negative correlation with FoS. This can be ascertained to the fact that with an increase in slope height, the FoS decrease and with the increase in cohesion and young's modulus of the weathered rock mass, the weathered layer becomes more stable/strong with respect to the topsoil leaving the weak residual soil layer vulnerable to sliding. The young's modulus of residual soil and the strength parameter of the soil-rock joint interface (cohesion and angle of internal friction) are almost uncorrelated or having no relationship with FoS.

Table 1 Summary of Slope Stability Database (Ray et al. 2019)

Statistical Parameters for Residual Soil					
S.No.	**Property**	**Mean**	**Standard Deviation**	**Relative Minimum**	**Relative Maximum**
1	Young's Modulus (MPa) E_s	69.72	17.65	16.77	122.67
2	Friction Angle (^{0}) Φ_s	32.174	6.291	13.3	51.047
3	Cohesion (kPa) C_s	19.5	0.200	18.9	20.1
Statistical Parameters for Weathered Layer (Rock Mass)					
S.No.	**Property**	**Mean**	**Standard Deviation**	**Relative Minimum**	**Relative Maximum**
1	Young's Modulus (MPa) E_r	35256.00	4301.00	22353	48159
2	Friction Angle (^{0}) Φ_r	42.14	5.44	25.82	58.46
3	Cohesion (kPa) C_r	7.44	4.03	3.41	11.47
Statistical Parameters for Joint interface between Residual Soil and Weathered Layer					

S.No.	Property	Mean	Standard Deviation	Relative Minimum	Relative Maximum
1	Cohesion (kPa) C_j	0.05	0.001	0.047	0.053
2	Friction Angle (^{0}) Φ_j	30.00	2.00	24	36
Slope Physical Parameter					
Slope Angle (α): 15^0, 30^0, 45^0, 60^0					
Slope Height (H): 50m, 100m, 150m, 200, 250m, 300m, 350m, 400m, 450m, 500m					
Residual soil depth (D): 0.5m, 1m, 2m, 3m, 4m, 5m, 7m, 9m, 12m, and 15m					

Table 2 Correlation matrix of the slope stability parameter

	α(^{0})	**H (m)**	**D (m)**	**Es (MPa)**	**Φs (^{0})**	**Cs (kPa)**	**Er (MPa)**	**Φr (^{0})**	**Cr (kPa)**
α(^{0})	1								
H (m)	0.00715	1							
D (m)	-0.00167	-0.01358	1						
Es (MPa)	0.00122	0.01562	0.01745	1					
Φs (^{0})	-0.02991	0.0414	-0.02109	-0.04173	1				
Cs (kPa)	-0.04456	0.02103	-0.01574	0.04054	0.01495	1			
Er (MPa)	-0.00594	-0.02455	0.05732	-0.07167	-0.00859	0.009728	1		
Φr (^{0})	-0.01349	0.07879	0.0076	0.02351	0.02589	0.083554	-0.08109	1	
Cr (kPa)	-0.00047	-0.02308	0.00865	0.022582	0.01046	-0.02068	-0.06785	0.02359	1
Cj (kPa)	-0.06443	0.02067	0.09423	-0.02652	0.06356	-0.00727	0.057505	-0.01176	0.061502
Φj (^{0})	0.03739	-0.09392	-0.10537	0.111417	0.00105	0.004913	-0.03417	-0.02553	-0.11242
FoS	-0.73448	-0.05091	-0.31331	0.008486	0.02604	0.030472	-0.04926	0.04307	-0.02531

FoS	Φj (^{0})	Cj (kPa)
		1
	1	-0.0658
1	-0.0043	-0.00834

3. ANN MODEL AND METHODOLOGY

ANNs are regarded as information processing systems that can learn, recall, and generalise from training data (Erzin and Cetin 2013; Lu and Rosenbaum 2003; Sakellariou and Ferentinou 2005). ANNs are mathematical model formed by a collection of numerous elementary processing units called neurons. Neurons are scrupulously interconnected computational units that have the potential to perform data processing and knowledge representation using extensive parallel computation (Verma et al. 2016; Yilmaz 2010). Due to its robust computational structure, ANN can be trained to model complex physical phenomenon (Pradhan and Lee 2010). Several ANN architectures have been used in geotechnical engineering applications ((Khandelwal and Singh, 2011; Khandelwal and Singh, 2013; Siddiqui et al. 2015; Khandelwal et al 2017; Khandelwal et al 2018; Qian et al. 2019) and particular slope stability assessment (Chakraborty and Goswami 2017; Choobbasti et al. 2009; Oh and Lee 2017; Zare et al. 2013).

3.1 NETWORK ARCHITECTURE

The fundamental building blocks of an ANN model are neurons which are complex mathematical processing units interconnected among themselves through weights and biases (Das et al. 2011). An ANN is generally developed using three primary layers, namely, input, hidden and output layer. In order to surmount nonlinearly separable problems like slope stability analysis, multilayer neural networks are much robust in contrast to single-layer neural networks as they are proficient in using the fusion of a linear transfer and sigmoidal function (Chakraborty and Goswami 2017; Zare et al. 2013). These multiple layers are positioned between the input and the output layer resulting in the formation of a Multilayer Perceptron (MLP) (Erzin and Cetin 2013; Kalantar et al. 2018; Oh and Lee 2017; Sakellariou and Ferentinou 2005). The intermediate layer(s) do not interact directly with the external environment; hence are called hidden layers. All the neurons are positioned into hidden and output layers, while the input layer remains free of neurons (Pradhan and Lee 2010). MLPs can be developed in such a way that it can accommodate multiple hidden layers. Nevertheless, there is hardly any advantage of utilising multiple hidden layers. Yilmaz (2010) observed that a single hidden layer MLP could approximate any function with a reasonable degree of accuracy provided there is an adequate number of nodes in the hidden layer. In some cases, the use of two hidden layers can be justified when the optimum number of nodes on a single hidden layer is too large. A typical ANN model used in this work is shown in Fig. 3.

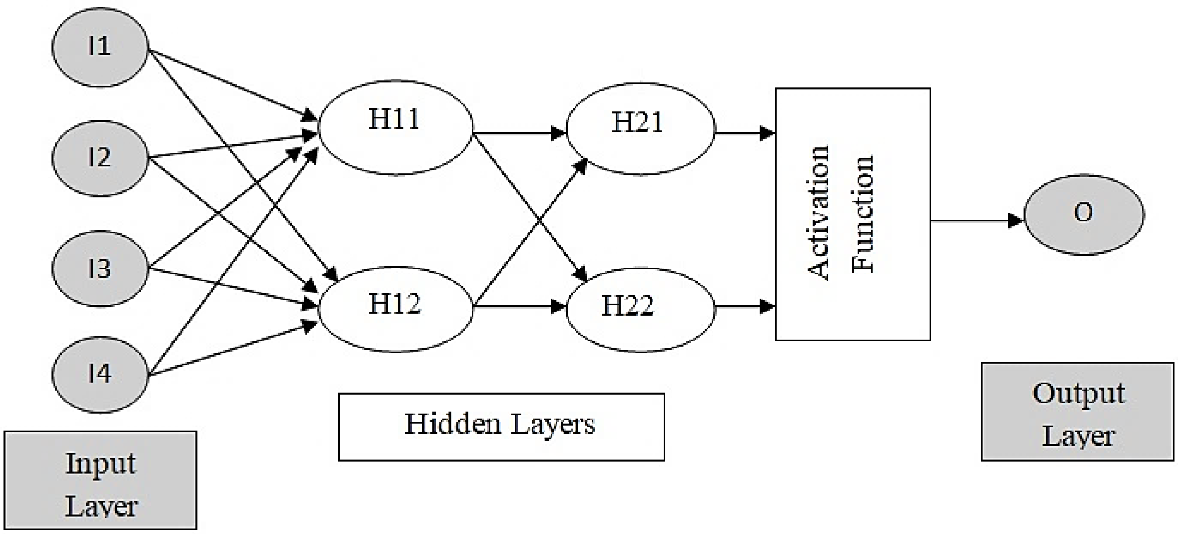


Fig. 3 The architecture of the MLP ANN model

The objective of the present study is to predict FoS from relevant geotechnical and physical parameters of residual soil slope. Feed-forward back-propagation neural network architecture is adopted here due to its suitability for this type of problem (Pradhan and Lee 2010; Yilmaz 2010; Zare et al. 2013). Input in the form of neurons compromise the input layer, and each neuron is attached to the neuron in the succeeding layer, i.e., the output of the neurons in the input layer is used as input for the neurons in the hidden layer, and similar attachment is present between successive hidden layers and the final output layer. Each attachment/junction of all the interconnected nodes carries an initial set of weight which is randomly distributed. When a value passes across an interconnection, it is multiplied by the assigned weight associated with that interconnection (Gomez and Kavzoglu 2005; Khandelwal et al. 2015). Each neuron has 'n' inputs and calculates its output 'a' using Eqn. (1).

$$a = f\left(\sum_{i=0}^{n} w_i p_i + b\right) \tag{1}$$

Where p_i is the i^{th} input, w_i is the i^{th} weight, b is the bias, and f is the transfer function or activation function for the neuron (Choobbasti et al. 2009; Khandelwal et al. 2015; Verma et al. 2016; Zare et al. 2013). The number of hidden layers and neurons in each hidden layer is updated according to the problem in order to minimise the overall error of the model.

3.2 TRAINING AND TESTING

The values of weights and thresholds in Eqn. (1), governs the behaviour of an entire neural network. Before operating an ANN model, it has to be trained appropriately. The training process involves the determination of optimum values of all the weights and biases of the network (Chakraborty and Goswami 2017; Rukhaiyar et al. 2018; Verma et al. 2016). The selection of training data is the most vital part of any AI techniques, and the training data must be representative of the whole dataset (Khandelwal et al. 2015; Trigila et al. 2015). By using a limited training set, the relationship cannot be learned appropriately where if the training set is too large, the generalisation capability cannot be verified. Also, using a too large training set may lead to over-fitting (Abdalla et al. 2015; Das et al. 2011). Various types of techniques and tools are available which can be used to obtain the suitable values of weights and biases of the ANN model (Oh and Lee 2017; Pradhan and Lee 2010; Yilmaz 2010). For the current work, optimum training of the network has been achieved in the Spyder V3.3.2 Platform (an open-source platform). Training algorithms are formulated to calibrate the weights and thresholds systematically by using the training data sets (Choobbasti et al. 2009; Das et al. 2011). The training process involves constant updating of the synaptic weights and threshold for minimising the Root Mean Square Error (RMSE) (Pradhan and Lee 2010). The network studies each set of input data and generates an output. The generated output is then compared with the expected output. Generally, there is a difference between the expected output and the network output during the training process. The resulted error is decreased by repeatedly adjusting the weights and threshold of the network. This way, the network calibrates its synaptic weights while working through the entire input and output datasets (Choobbasti et al. 2009; Kalantar et al. 2018). After running through all the possible neural networks, the RMSE given by Eqn. (2) is compared with the maximum predefined tolerance. If it is higher than the maximum predefined tolerance, a new epoch (a run through all training input-output sets) is processed by adjusting the synaptic weights in order to further reducing the error function. This is an iterative process and is continued until the error function of the network achieves the desired tolerance level. This is known as the backpropagation algorithm (Cho 2009; Choobbasti et al. 2009; Das et al. 2011; Khandelwal et al. 2015; Pradhan and Lee 2010). The ultimate objective is to minimise the RMSE of the network, which is defined as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{O_i} - \mathrm{I_i})^2}{\mathrm{n}}} \tag{2}$$

Where O_i is the output corresponding to the i^{th} data point in the training set by the network, I_i is the actual output as considered in the target set, n is the number of data points considered in training data-set. The model producing the least value of RMSE is considered since it is presumed that the prediction equation accomplishes a close relationship and the training process is terminated (Oh and Lee 2017; Siddiqui et al. 2015). Once the ANN is adequately trained, it acts as a black-box model that can correlate complex input and output datasets. The ANN model is shown in Fig. 3 can accept 'n' input parameters to produce a single (FoS) output. An ANN model can be regarded as robust if it gives a lower value of fitness function for both training and testing datasets (Rukhaiyar et al. 2018). Once training is complete, testing can be done for the network. During testing, the observed values from numerical simulations are fed to the trained network in order to predict the output values (Sakellariou and Ferentinou 2005).

3.3 MODEL EVALUATION

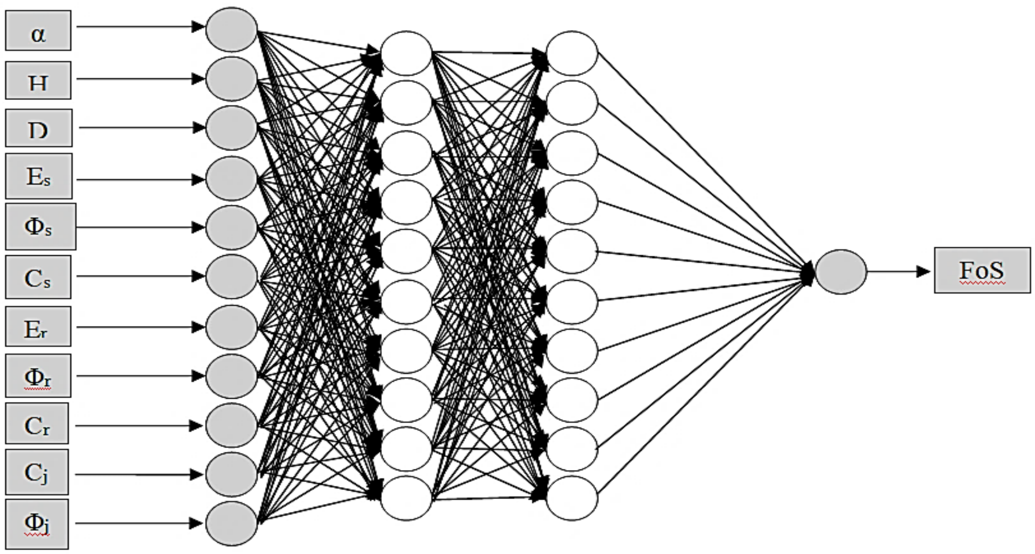
The Coefficient of Determination (R^2) curve is usually used to assess the efficacy of the ML models (Kalantar et al. 2018; Qi and Tang 2018). The R^2 value describes the goodness of fit of an ML model, which is a statistical tool for judging the precision of the regression model in predicting the actual data points. An R^2 value of 1 indicates that the regression prediction perfectly fits the data. Another factor which can be utilised to evaluate the model performance is the residual error.

When an ANN model is developed, all the predicted output points do not necessarily pass through the original/expected points. The residual plot displays how each data point is adjacent vertically from the original point to the predicted outcome from the model. Utilising the residual error, the effectiveness of the model prediction can be ascertained. The function VAF which calculates the 'Variance Accounted For' between the measured and predicted values could also be used for model evaluation. The VAF is often used to verify the correctness of a model by comparing the measured values with the predicted values of the model. If VAF is 100% and RMSE is 0, the model is treated as excellent. If there is a difference between the measured and predicted values, the VAF will be lower than 100%, and RMSE will be more than 0.

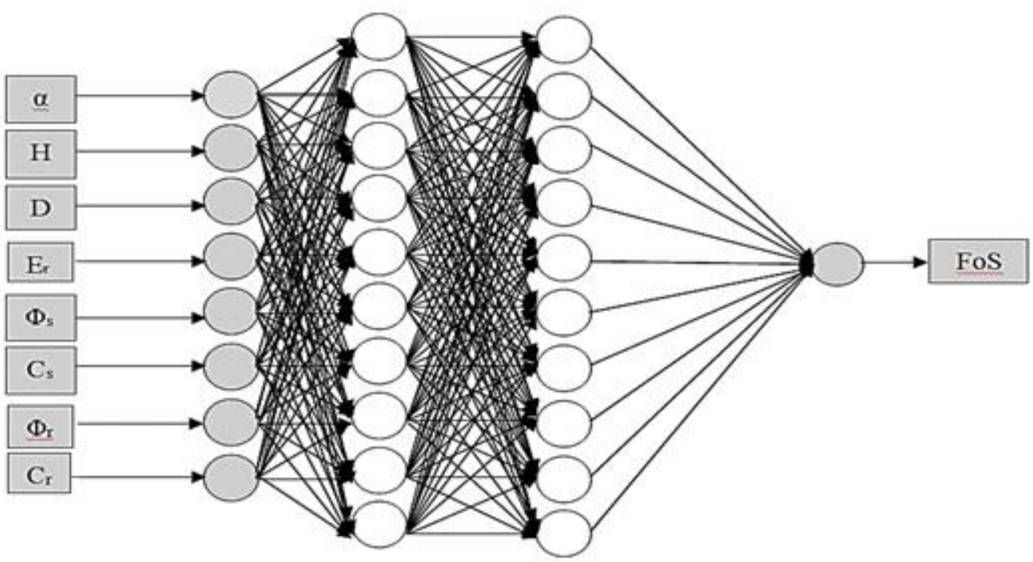
3.4 METHODOLOGY

In this research, the results of numerical simulation using different physical and geotechnical parameters of the Himalayan residual soil slope by Ray et al. (2019) were utilised for developing the prediction model by ANN. In the proposed model for slope stability prediction, several vital parameters listed in Table 1 were adopted as input variables, whereas the FoS was taken as the output parameter. The ANN model used for predicting the FoS was developed in the Spyder V3.3.2 Platform. A four-layer feed-forward back-propagation neural network was developed as the prediction model having ten neurons each in two hidden layers and one neuron in the output layer for predicting the FoS. For the cross-validation procedure, the entire data set used for the development of the prediction model was divided into two distinct sets, i.e., training and testing. In ML techniques, optimisation analysis is generally employed to determine the percentage of the training and testing data set (Qi and Tang 2018; Zare et al. 2013). After going through the optimisation analysis for the present analysis, approximately 80% (320 cases) of the entire dataset was incorporated in the training set, and the remaining 20% (80 cases) was incorporated in the testing set. The training dataset was separated from the entire data, and a separate dataset consisting of these 320 data is made. During the subsequent training process, the separated dataset was used every time in order to reduce the RMSE and obtained the desire MLP.

The present analysis is performed by developing two different ANN models (Fig. 4**).** The first ANN model (ANN1) has all eleven input variables, and the second ANN model (ANN2) has eight input variables – slope angle, slope height, residual soil depth, residual soil cohesion and the angle of internal friction, weathered rock mass cohesion and the angle of internal friction, and the young's modulus of the weathered rock mass. The input parameters considered in ANN2 model is based on the higher importance/significant parameters obtained from correlation analysis, as shown in Table 2.



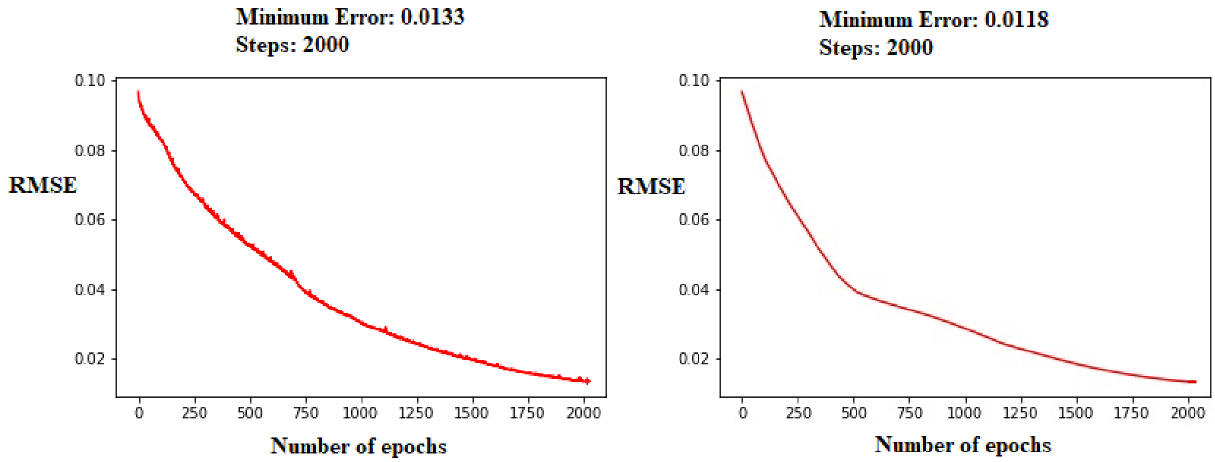
(a) The network architecture of ANN1



(b) The network architecture of ANN2

Fig. 4 Architecture of the two MLP ANN models

During the training process, the number of epochs was gradually increased from 500 to 3000. Repeated iteration is performed using the Levenberg-Marquardt backpropagation method until error is minimised to an acceptable value. Based on the error analysis, the number of epochs was set to 2000, and the minimum RMSE value achieved for both the ANN models are shown in (Fig. 5).



(a) (b)

Fig. 5 Training based on RMSE for predicting the residual slope failure (a) ANN1 (b) ANN2

The output parameter for each ANN model is the FoS. Previous works by (Verma et al. 2016; Yilmaz 2010) adopted hyperbolic tangent and sigmoid activation functions for hidden layers. However, there is a limitation of using these functions. The hyperbolic tangent and sigmoid activation functions, due to the vanishing gradient problem, are not suitable for networks having multiple hidden layers. Both of these functions generally get saturated during the iterative process. The limited sensitivity and saturation of these activation functions evolve regardless of whether the summed activation from the individual nodes provided as input, contains useful information or not. As a result, it turns out to be a challenge for the training process to continue adapting the weights for improving the efficiency of the network (Goodfellow et al. 2017). The rectified linear activation function (ReLU) surpasses the vanishing gradient problem, thus allowing the model to learn faster and perform better. For the current study, the ReLU activation function is used for the hidden layer, whereas a linear bias transfer function is used for the output layer.

Based on the accuracy of generated results, the most suitable neural network architecture was deduced by training and testing different combinations of hidden layers and associated neurons. After going through various network combinations, the network with 11-10-10-1 architecture for ANN1 and 8-10-10-1 architecture for ANN2 (Fig. 4) is selected corresponding to minimum RMSE of 0.0133 and 0.0118, respectively (Fig. 5). The selected ANN1 and ANN2 network has a learning rate and momentum of 0.69, 0.021 and 0.78, 0.016, respectively. The network architecture of both the ANN models is tabulated in Table 3.

Table 3 Network architecture of ANN models

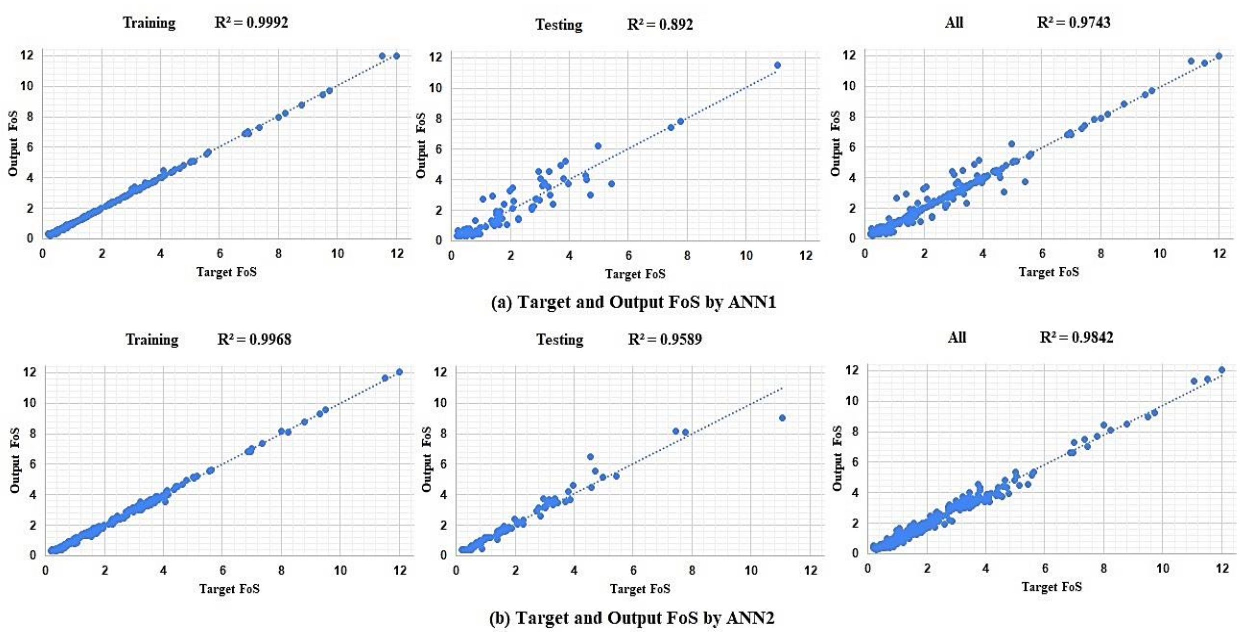
Model	**ANN1 (MLP 11-10-10-1)**	**ANN2 (MLP 8-10-10-1)**
No. of epochs	2000	2000
Training Error	0.0133	0.0118
Prediction Error	0.06566	0.04375

Training Algorithm	Stochastic Gradient Descent	Stochastic Gradient Descent
Hidden Activation	ReLU	ReLU
Output Activation	Linear	Linear
No. of training sets	320	320
No. of testing sets	80	80
Learning Rate	0.69	0.78
Momentum	0.021	0.016

Once training is complete, testing can be initiated. During the testing phase, the input parameters for various slope configurations from Ray et al. (2019) are fed into the network for predicting the FoS accordingly. These obtained FoS results are then compared with the corresponding numerical simulation results for efficiency calculation.

4. RESULTS AND DISCUSSION

A comparison of FoS values derived from the numerical simulation with that of the values predicted from the two ANN models is depicted in Fig. 6 for the training and testing phase. The coefficient of correlation (R^2) between the predicted and measured values indicates an excellent prediction performance of the model. There is hardly any significant difference between the performances of ANN1 and ANN2 training models. It can be inferred that the performance of the training models did not change drastically when the number of the input parameters were reduced to eight. However, a significant difference in R^2 value is observed during the testing phase (Fig. 6). The R^2 value of ANN2 during testing phase shows superior results as compared to ANN1 due to the use of variables having higher correlation factor which indicates the superiority of ANN2 model from ANN1 in predicting the values of FoS.



(a) Target and Output FoS by ANN1

(b) Target and Output FoS by ANN2

Fig. 6 Targeted and output FoS for both the ANN models during training, testing and entire data set

As employed by (Erzin and Cetin 2013), the RMSE, represented by Eqn. (2), and variance account for (VAF), represented by Eqn. (3) were computed for studying the performance and the prediction capacity of the predictive models. The performance indices obtained from the developed ANN models are presented in Table 4. The results indicate almost similar RMSE and VAF value during the training phase of ANN1 and ANN2. However, a significant difference in RMSE and VAF is observed during the testing phase. The RMSE and VAF of ANN2 during testing phase shows superior results as compared to ANN1 due to the maximum accounted variance during calculation and the use of variables having higher correlation factor which indicates the superiority of ANN2 model in predicting the outcome.

$$VAF = \left[1 - \frac{var(measured\ value - predicted\ value)}{var\ (measure\ value)}\right] X\ 100 \tag{3}$$

Table 4 Performance indices of the ANN models

Model	Data	R^2 (%)	RMSE	VAF (%)
ANN1	Training Set	99.92	0.0133	99.89
	Testing Set	89.20	0.0656	88.43
ANN2	Training Set	99.68	0.0118	99.85
	Testing Set	95.89	0.0462	98.76

Fig. 7 depicts a comparison between the predicted and calculated FoS of ANN1 and ANN2 from the data obtained from the numerical simulation. It can be inferred that the prediction of the ANN2 model is relatively closer to the calculated values as compared to the ANN1 prediction. The use of higher importance/significant input parameters based on correlation analysis and scaling effect resulted in better performance of ANN2, which could be attributed to the sufficient number of data in the solution space of ANN2.

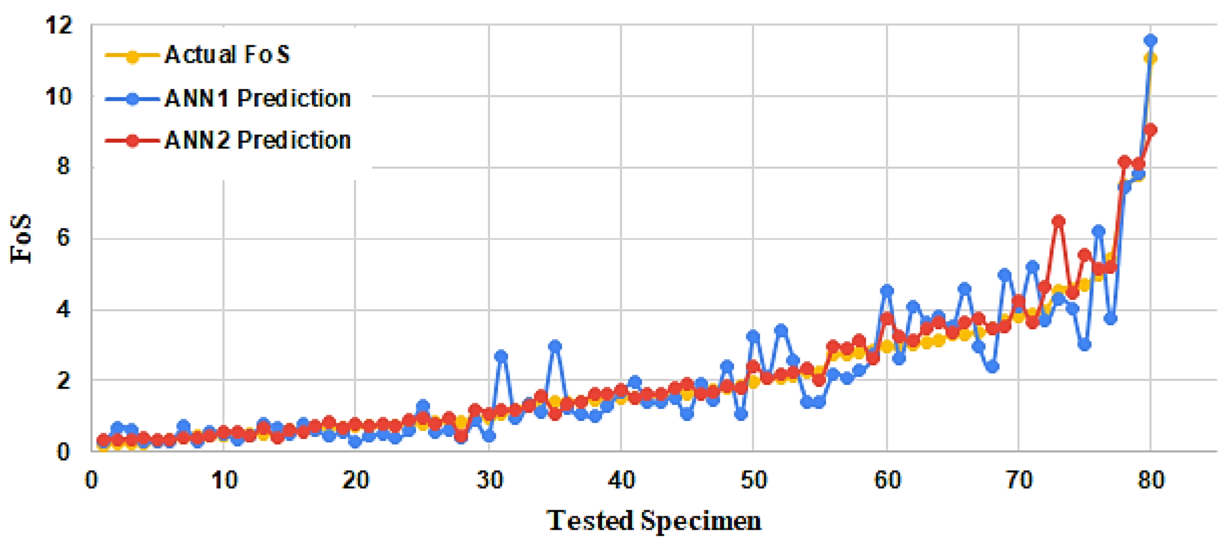


Fig. 7 Prediction of FoS for test data for different ANN methods

In order to examine the extent of deviation of the observed value from the actual value of FoS, residual error (the difference between any data point and the regression line) of the ANN models were calculated. The deviation of the predicted values of ANN1 and ANN2 models from the values obtained from numerical simulation is shown in Fig. 8. When compared, the deviation intervals of the ANN1 (-1.86 to 1.65) model does not vary much from the ANN2 (-1.89 to 1.95) model. However, when the percentage deviation of several tested observations in each error class is analysed, it can be concluded that the dispersion of the ANN2 model is less compared to the ANN1 model (Table 5) indicating a higher accuracy of the ANN2 model.

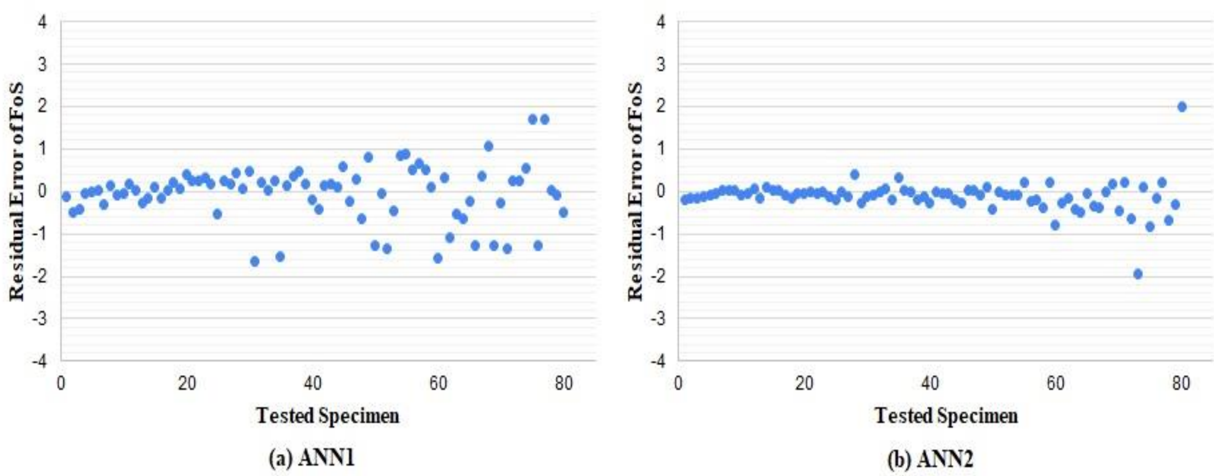


Fig. 8 Residual error of prediction for different ANN models

Table 5 Percentage of test results for different error class for ANN models

Residual Error Class	% number of test results for ANN1 model	% number of test results for ANN2 model
0 to ±0.5	68.75	91.25
±0.5 to ±1	15	6.25
> ±1	16.25	2.5

The extent to which an ANN could be useful for anticipating the state of slope stability depends upon the available input data. With an increase in the number of input data, it is expected that the prediction will also improve. However, the use of more extensive training data sets can sometimes result in the training algorithm to stall, becoming stuck at a local error minimum (Flood and Kartam 1994). The ANN model proposed in this study considered all the available slope physical and geotechnical parameters. It is believed that several other factors could also be influential, for example, the history of slope movement, engineering disturbance, climate, and vegetation. However, the lack of measurement prevents their direct incorporation. Consequently, caution needs to be exercised in the practical implementation of a trained ANN model, recognising the limitations of the available input data. From the analysis, it can be concluded that the FoS value of the Shiwalik slopes could be easily predicted with an acceptable degree of accuracy during the preliminary stage evaluation of complex Himalayan residual soil slope from readily determining soil properties and slope parameters using the trained ANNs values.

5. CONCLUSIONS

In this study, attempts were made to develop an AI model that can be employed for estimating the FoS value of Shiwalik slopes of the Himalayas. For this purpose, the FoS values obtained from numerical analysis of 400 residual soil slopes having different slope mechanical and physical parameters were utilised. Two different ANN models were developed using various physical and geotechnical parameters which influences the overall stability of a residual slope. The ANN1 model has all eleven parameters affecting the slope, while the ANN2 model incorporates only the significant parameters based on correlation analysis. Based on the results obtained, the following observations and conclusion are made:

- ANN can act as an excellent prediction tool, especially for anticipating the behaviour of residual slopes. It was observed that both the ANN models could predict the FoS of the residual slope with close agreement over numerical modelling. Since the input data is obtained from the analysis of stochastic geotechnical parameters of the natural slope, the model prediction is still around 90%. Looking into the intricacy of the residual soil slope problem, the results achieved from the models are highly encouraging and satisfactory, which gives a reasonable expectation for the practical implementation of these models.
- Various performance indices like RMSE, R^2, and VAF were evaluated in order to judge the prediction performance of the developed models. Both the models have displayed excellent prediction performance with ANN2 outcast ANN1 substantially in all performance parameters. The performance level achieved by both the ANN models displays the utility of using ML tools in handling the various soil engineering projects associated with various levels of uncertainties. Thus, the utilisation of neural networks can provide alternative approaches and methodologies for minimising the potential inconsistency due to correlations.
- Analysis of residual error of the predicted values from the models indicated almost similar variation for the ANN1 (-1.86 to 1.65) and ANN2 (-1.89 to 1.95). However, a critical analysis of the residual error plot indicates that the error dispersion of the ANN2 model is less compared to the ANN1 model.

Finally, continued research is required in developing new models focusing on a variety of factors that ultimately affects the occurrences of a landslide. One of the benefits of utilising ANN is that it can absorb new patterns which are not previously used during training dataset. ANN can also upgrade its database with the inclusion of more training data sets over time and can process the upgraded information in a parallel way. Hence, the approach proved to be economical and more manageable in contrast to tedious and expensive experimental work.

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