

CHAPTER 6

SLOPE STABILITY ANALYSIS USING ARTIFICIAL NEURAL NETWORK

6.1 Introduction

In the past few decades, advances in Machine Learning (ML) techniques have resulted in developing sophisticated models capable of modelling extremely complex multi-factorial problems like slope stability analysis. The ability to handle nonlinear problems and the ease of updating the dataset makes them the perfect choice for developing a slope stability predicting model. 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 evaluate the FOS of the residual soil slopes in Lesser Himalaya. Data obtained from numerical analysis of a residual soil slope (Chapter 5) was used to develop the ANN models. Various performance indices like the coefficient of determination (R^2), residual error, Root Mean Square Error (RMSE), the Variance Accounted For (VAF), and learning rate has been used for assessing the efficacy of the developed ANN models. Based on the ANN analysis, the relative importance ranking for the input variables was also obtained.

6.2 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 2010b). MLPs can be developed so that they 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, using 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. 6.1.

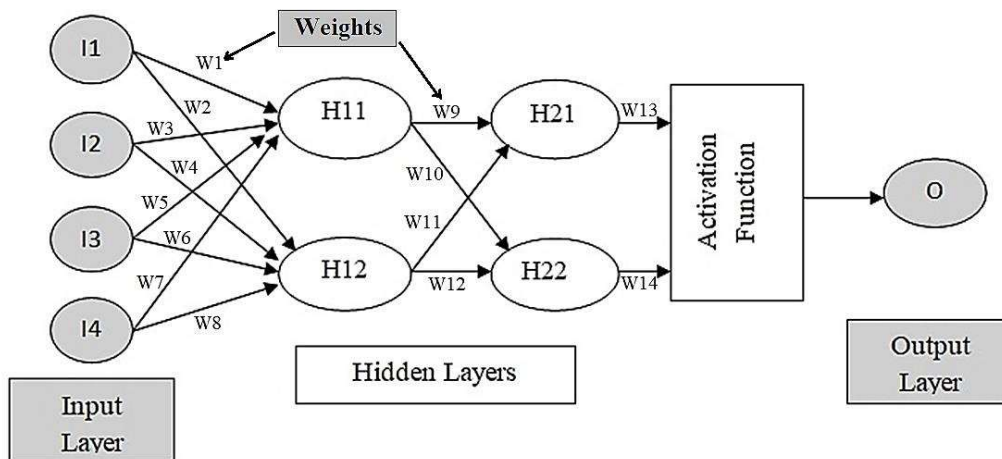


Fig. 6.1. The network architecture of an MLP ANN model

The objective of the present study is to predict the factor of safety 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 2010b; Yilmaz 2010; Zare et al. 2013). Input in the form of neurons compromise the input layer. 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. Similar attachment is present between successive hidden layers and the final output layer. Each junction of all the interconnected nodes carries an initial set of weights which is randomly distributed as shown in Fig. 6.1. 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. 2015a). Each neuron has n inputs and calculates its output a using Eqn. 6.1.

$$a = f\left(\sum_{i=0}^n w_i p_i + b\right) \quad (6.1)$$

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. 2015a; Verma et al. 2016; Zare et al. 2013). The activation functions of the input layer are usually defined as the identity function. While, the activation functions in the hidden and output layers can be a mathematical function which continuous first and second-order derivatives (i.e., logistic sigmoid, hyperbolic tangent, exponential and sine). Each neuron performs a weighted sum of its inputs and passes it through a transfer function f to produce its output. For each neural layer in an MLP network, there is also a bias term. A bias is a neuron whose activation function is permanently set to 1. Like other neurons, a bias connects to the neurons in the layer above via a weight, often called a threshold. The neurons and biases are arranged in a layered feedforward network. The network has a simple interpretation as an input-output model, with the weights and thresholds as the free (adjustable) parameters of the model. Such networks can model functions of almost arbitrary complexity with the number of layers and the number of units in each layer. Important issues in MLP design include the specification of the number of hidden layers and the number of units in these layers (Bishop 1995).

Others include the choice of activation functions and methods of training. 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.

6.2.1 Training, Testing and Validation

The values of weights, bias and activation function in Eqn. 6.1 governs the behaviour of an entire neural network. Before operating an ANN model, it has to be trained appropriately. The training process involves determining 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 ML technique, and the training data must be representative of the whole dataset (Khandelwal et al. 2015a; Trigila et al. 2015). The relationship cannot be learned appropriately if a limited training set is used, whereas if the training set is too large, the generalisation capability cannot be verified. Also, using a too large training dataset 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 2010b; Yilmaz 2010).

Statistica Software (Stadsoft 2011) has been used to train the network optimally. Training algorithms are formulated to calibrate the weights and bias 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 bias for minimising the RMSE (Pradhan and Lee 2010b). 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 resulting error is decreased by repeatedly adjusting the weights and bias 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 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 to reduce the error function further. It is an iterative process and continues 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. 2015a; Pradhan and Lee 2010b). The ultimate objective is to minimise the RMSE of the network, which is defined as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (O_i - I_i)^2}{n}} \quad (6.2)$$

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 the 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. 6.1 can accept n input parameters to produce a single (FOS in this case) output. An ANN model can be regarded as robust if it gives a lower fitness function value 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 to predict the output values (Sakellariou and Ferentinou 2005). The accuracy of the model on the test data gives a very rough estimate of how accurate the model will be when presented with new, previously unseen data. After finishing training and testing, finally, validation is performed.

During validation, the new and previously unseen data is used with the trained network to find the outcome. The obtained outcomes will be the final output of the developed model for prediction.

6.2.2 Model Evaluation

Various performance indices like the coefficient of determination (R^2), RMSE, VAF, and the learning rate is used for assessing the efficacy of ML models (Bharati et al. 2021; Bharti et al. 2021; Kalantar et al. 2018; Ray et al. 2020b; Verma et al. 2016). The R^2 value is a statistical tool for describing the goodness of fit of an ML model by judging the precision of the developed model in predicting the actual data points (given in Eqn. 6.3). The R^2 value lies between 0 and 1, where 0 indicates that the developed model does not fit the given dataset and 1 indicates that the developed model perfectly fits the dataset provided.

$$R^2 = 1 - \frac{\sum_{i=1}^n (\text{measured value}_i - \text{predicted value}_i)^2}{\sum_{i=1}^n (\text{measured value}_i - \text{mean of output values})^2} \quad (6.3)$$

The residual error plot can also be utilised to evaluate the performance of the developed models. When an ML model is developed, all the output points predicted by the model do not necessarily pass through the original points. The deviation of the predicted outcome from the actual value is displayed through a residual error plot. The deviation is displayed as the vertical distance between the predicted outcome and actual value in the residual error plot (the difference between any data point and the regression line as given in Eqn. 6.4). Models possessing the least and concentrated residual errors are superior to models having higher and spread-out residual errors.

$$\text{Residual Error} = |\text{measured value}_i - \text{predicted value}_i| \quad (6.4)$$

In RMSE, the errors are squared before they are averaged, as shown in Eqn. 6.2 (where n is the number of data points considered). It implies that the RMSE assigns a higher weight to more significant errors. This indicates that RMSE is more helpful when significant errors are present

and drastically affect the model's performance. The value of RMSE ranges from zero to infinity; however, the lower the value, the better is the performance of the model.

The function VAF, which calculates the variance between the predicted and measured values, has also been used for evaluating the predicting performance of the developed ML model (Eqn. 6.5). The VAF is often used to verify the correctness of a developed model by comparing the model's predicted values with the corresponding measured values. All those models whose RMSE is 0 and VAF are 100% are treated as excellent. For those models where there is a difference between the predicted and measured values, the RMSE will be more than 0, and the VAF will be lower than 100%.

$$\text{VAF} = \left[1 - \frac{\text{var}(\text{measured value} - \text{predicted value})}{\text{var}(\text{measure value})} \right] \times 100 \quad (6.5)$$

Learning rate is a hyper-parameter that controls the weights of the ML models with respect to the loss gradient. It represents how rapidly the ML algorithms update the concepts it has learned, which in turn decides how fast or how slow a model arrive at some conclusion. A smaller learning rate requires more training epochs (requires more time to train) due to the smaller changes made to the weights in each update, whereas a larger learning rate results in rapid changes and require few training epochs.

6.3 Development of ANN Prediction Models

The selected input data is normalised between 0 to 1 using the min-max normalisation technique before initiating the network development process. Normalisation is often applied as part of data preparation for machine language. Normalisation aims to change the values of numeric columns in the dataset to use a standard scale without distorting differences in the ranges of values or losing information (Das and Basudhar 2006). This is highly useful in the current study since there is a marked variation between the ranges of different input variables. Normalisation avoids

these problems by creating new values that maintain the general distribution and ratios in the source data while keeping values within a scale applied across all numeric columns used in the model. Normalisation helps in speeding up the learning rate and finally leads to faster convergence. Rescaling to the [0,1] interval is done by shifting the values of each feature so that the minimum value is 0 and then dividing by the new maximal value (which is the difference between the original maximal and minimal values) (Eqn. 6.6). The values of a particular input parameter are transformed using the following formula:

$$Z = \frac{x - \text{mean}(x)}{[\text{max}(x) - \text{min}(x)]} \quad (6.6)$$

The ANN model to predict the FOS was developed in Statistica Software (StatSoft 2011). In this study, a three-layer feed-forward back-propagation Multilayer perceptron was developed as the prediction model having variable neurons in the hidden layer and one neuron in the output layer for predicting the FOS. Multilayer perceptrons are feedforward neural networks having at least three layers of neurons, including an input layer, at least one hidden layer and a single output layer (McClelland et al. 1986).

The neural network architecture comprises two important tools, the training algorithm and the activation function of neurons. The Broyden-Fletcher-Goldfarb-Shanno (BFGS) training algorithm is used in the study, which requires a smaller number of iterations due to its fast convergence rate and smart search criteria (Quraishi and Mouazen 2013). The activation function of the hidden and output layer neurons is very crucial in deciding the desired neural network architecture, and it transforms the transmitted information from the previous layer to the subsequent layers by applying its mathematical function. Several networks can be trained simultaneously by opting a range of the number of neurons within the hidden layers and the desired transfer function to the hidden and output layer of the model to select the best ANN model.

Various transfer functions that have been used during the iteration process includes identity, logistic, tanh, exponential and sine. To assess the performance of the several developed MLPs, RMSE, which is the square root of the mean of the squared differences between actual outcomes and predictions, is used.

The entire dataset used to develop the prediction model was divided into training, testing, and validation for the cross-validation procedure. In ML techniques, optimisation is generally employed to determine the percentage of the training and testing dataset (Zare et al. 2013). After going through the optimisation for the present analysis, approximately 70% (randomly selected) of the entire dataset was incorporated in the training set, and the remaining 30% was divided equally between the testing and validation set. The training dataset (70%) was separated from the entire data for the subsequent training process. The separated dataset (70%) was used every iteration to reduce the RMSE and obtain the desired MLP.

The present analysis is performed by developing two different ANN models. The first ANN model (ANN1) corresponds to the numerical simulations performed for the residual slope under natural prevailing geomaterial condition, i.e., the input geotechnical parameters of the residual soil, soil rock interface and the weathered rock mass were obtained from laboratory investigations of collected disturbed samples (as given in Section 5.3.1). A total of fifteen independent input variables were identified for neural network analysis (Table 5.7). However, in order to increase the accuracy of the neural network, eight significantly important input variables (slope angle; slope height; residual soil depth; soil rock interface friction angle; residual soil angle of internal friction, unit weight, cohesion and young's modulus) out of the fifteen independent input variables were identified based on correlation analysis (variables having correlation coefficient > 0.1 in Table 5.7)

and were used for developing the neural network model. The developed ANN1 model is complementary to the developed hazard chart for quick identification of landslide vulnerability.

The second ANN model (ANN2) corresponds to the numerical simulations performed for the residual slope under remoulded geomaterial conditions. The input geotechnical parameters of the remoulded residual slope, soil rock interface and weathered rock mass were obtained from laboratory investigations of collected disturbed and remoulded samples (as given in Section 5.3.2). A total of seventeen independent input variables were obtained for neural network analysis (Table 5.9). However, in order to increase the accuracy of the neural network, nine significantly important input variables (slope angle; slope height; residual soil depth; water content and % fines of residual soil; residual soil angle of internal friction, unit weight, cohesion and young's modulus) out of the seventeen independent input variables were identified based on correlation analysis (variables having correlation coefficient > 0.1 in Table 5.9) and were used for developing the neural network model. The developed ANN2 model is complementary to the developed hazard chart for the detailed identification of landslide vulnerability.

6.3.1 ANN1 Model for Quick Landslide Hazard Identification

Eight significantly independent parameters (correlation coefficient > 0.1) were identified from the correlation analysis of fifteen independent slope physical and geotechnical parameters (Table 5.7). Numerical simulations of 400 slope models (Section 5.3.1) were considered input parameters for the neural network. The selected eight input parameters are represented as the input layer, while the FOS is represented as the output layer in the developed ANN1 architecture. The most suitable neural network architecture was deduced by training, testing and validating different combinations of hidden layers and associated neurons. A single hidden layer having a range of 2–15 neurons have been opted to train the neural network model. The number of neurons in the rest

two layers, i.e., input layer and output layer, are constrained to the number of input variables and output variables, respectively (Ghiasi et al. 2016). The normalisation of the input data was performed, and the training process was initiated by randomly varying the number of neurons and their associated weights. The network with 8-12-1 architecture (eight neurons in the input layer, twelve neurons in a single hidden layer and one neuron in the output layer) is selected based on maximum training performance and minimum training error for the ANN1 model after simulation of various network combinations (Table 6.1). The selected ANN1 model has a learning rate and momentum of 0.94 and 0.012, respectively, and its architecture is shown in Fig. 6.2.

Table 6.1: Identification of best MLP for ANN1 during the training process

Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
MLP 8-6-1	0.983	0.945	0.934	0.055	0.233	0.199	BFGS 31	SOS	Tanh	Exponential
MLP 8-9-1	0.976	0.949	0.913	0.076	0.215	0.226	BFGS 71	SOS	Logistic	Sine
MLP 8-2-1	0.884	0.901	0.886	0.360	0.404	0.305	BFGS 18	SOS	Exponential	Exponential
MLP 8-8-1	0.931	0.954	0.914	0.218	0.190	0.231	BFGS 30	SOS	Logistic	Identity
MLP 8-12-1	0.977	0.966	0.915	0.073	0.145	0.223	BFGS 52	SOS	Logistic	Tanh
MLP 8-14-1	0.893	0.910	0.881	0.333	0.369	0.330	BFGS 9	SOS	Identity	Exponential
MLP 8-8-1	0.954	0.953	0.905	0.147	0.209	0.246	BFGS 30	SOS	Logistic	Identity
MLP 8-3-1	0.965	0.938	0.902	0.112	0.260	0.170	BFGS 27	SOS	Tanh	Tanh
MLP 8-6-1	0.890	0.903	0.880	0.346	0.405	0.341	BFGS 17	SOS	Exponential	Exponential
MLP 8-8-1	0.967	0.940	0.895	0.106	0.257	0.275	BFGS 34	SOS	Tanh	Tanh
MLP 8-7-1	0.843	0.934	0.868	0.481	0.269	0.353	BFGS 3	SOS	Sine	Exponential
MLP 8-7-1	0.916	0.929	0.879	0.269	0.304	0.331	BFGS 33	SOS	Sine	Exponential
MLP 8-7-1	0.914	0.876	0.849	0.021	0.165	0.380	BFGS 76	SOS	Tanh	Exponential
MLP 8-5-1	0.886	0.912	0.885	0.359	0.363	0.315	BFGS 16	SOS	Exponential	Exponential

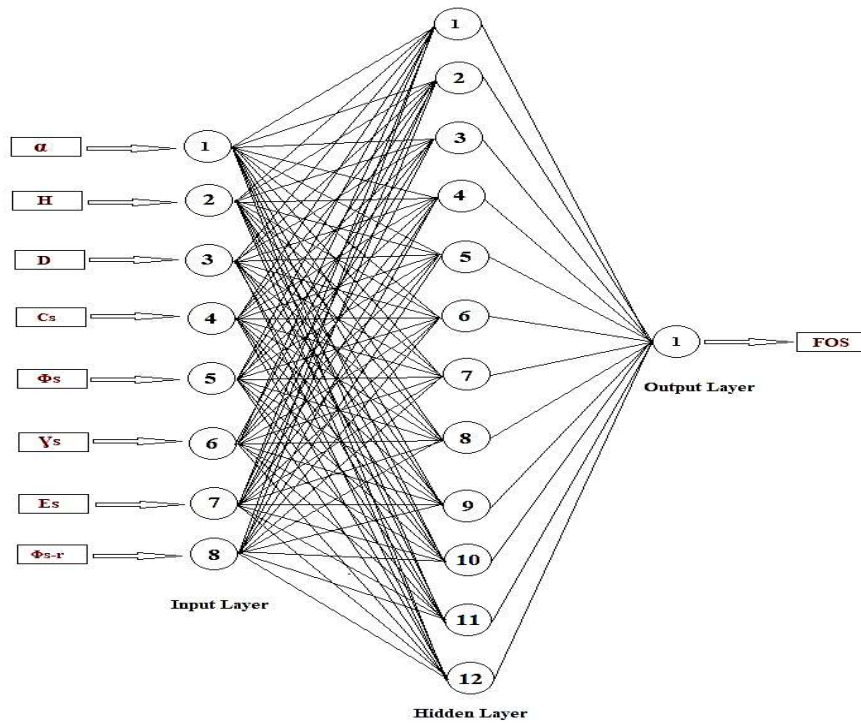


Fig. 6.2. Network architecture (MLP 8-12-1) of the developed ANN1 model

During the training process, the number of epochs (iterations) is gradually increased from 1 to 85 (Fig 6.3). Repeated iteration is performed using the Levenberg–Marquardt backpropagation method until error is minimised to an acceptable value (Table 6.1). Based on the error analysis, the number of epochs was set to 47, and the minimum RMSE value of 0.000403 was achieved.

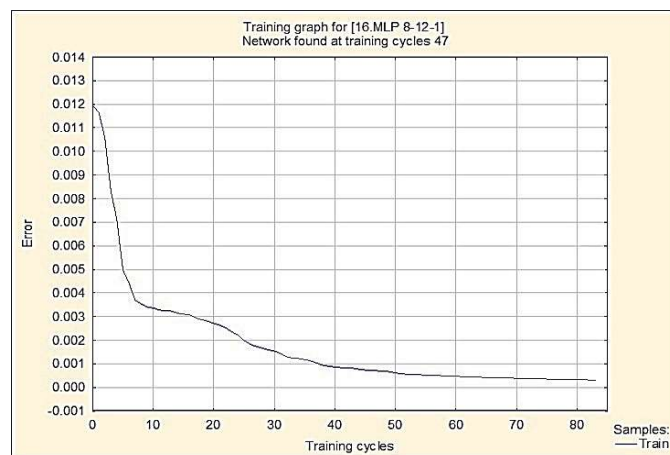


Fig. 6.3. Training RMSE curve of the selected MLP 8-12-1 for ANN1 model

Testing and validation have been performed after the network training phase is completed. The input parameters for various slope configurations are fed into the network for predicting the corresponding FOS. The predicted FOS are compared with the corresponding numerical simulation results for efficiency calculation. A comparison of FOS from the numerical simulation (Target FOS) with predicted from the ANN1 model (Output FOS) is depicted in Fig. 6.4 for the training, testing and validation phase.

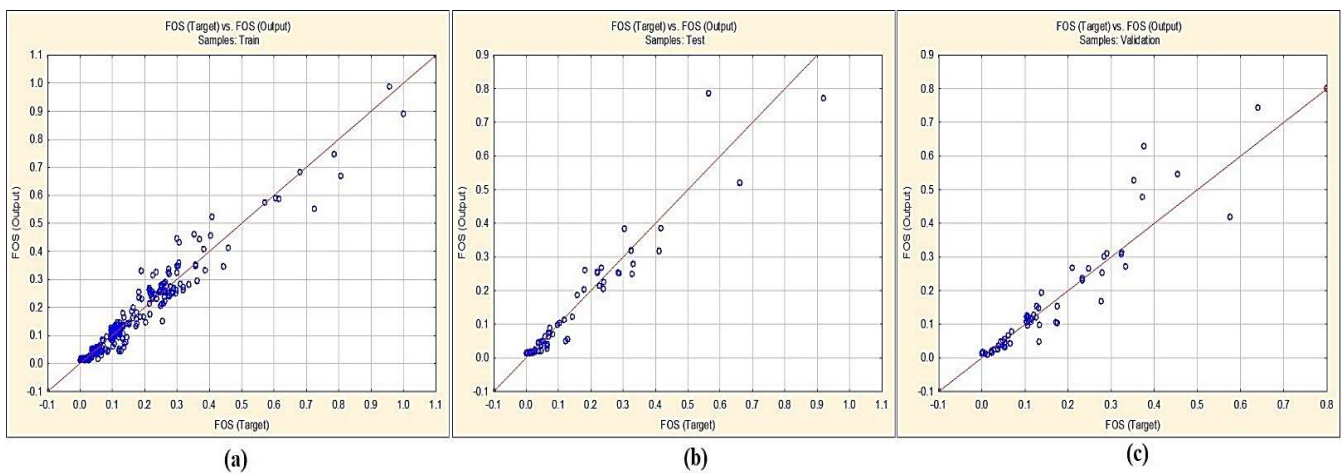


Fig. 6.4. Targeted and output FOS for the ANN1 model during training, testing, and validation phase

The coefficient of determination (R^2) between the target and predicted values indicates a good prediction performance of the model. The RMSE and VAF were computed for studying the performance and the prediction capacity of the developed predictive model. Various performance indices obtained from the developed ANN1 model is presented in Table 6.2. The learning rate curve of the selected MLP during the training and validation phase is shown in Fig. 6.5.

Table 6.2: Performance indices of the developed ANN1 model

Model	Data	R^2 (%)	RMSE	VAF (%)	Learning Rate
ANN1 (MLP 8-12-1)	Training Set	95.09	0.000403	98.74	0.94
	Testing Set	92.95	0.00143	94.52	0.92
	Validating Set	88.25	0.00217	93.30	0.89

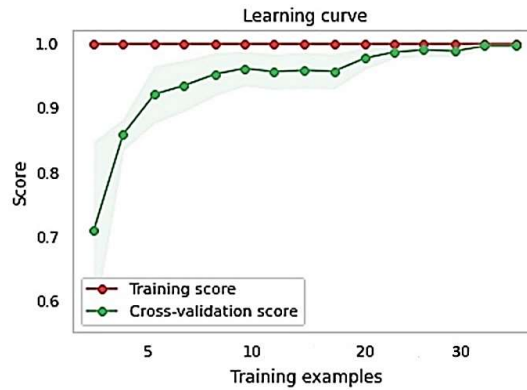


Fig. 6.5. Learning rate curve for training and validation phase of the developed ANN1 model

Fig. 6.6 depicts a comparison between the predicted FOS obtained from the ANN1 model with that of the target FOS obtained from the numerical simulation. It can be inferred that the prediction of the ANN1 model is relatively closer to the target values and within an acceptable level of confidence.

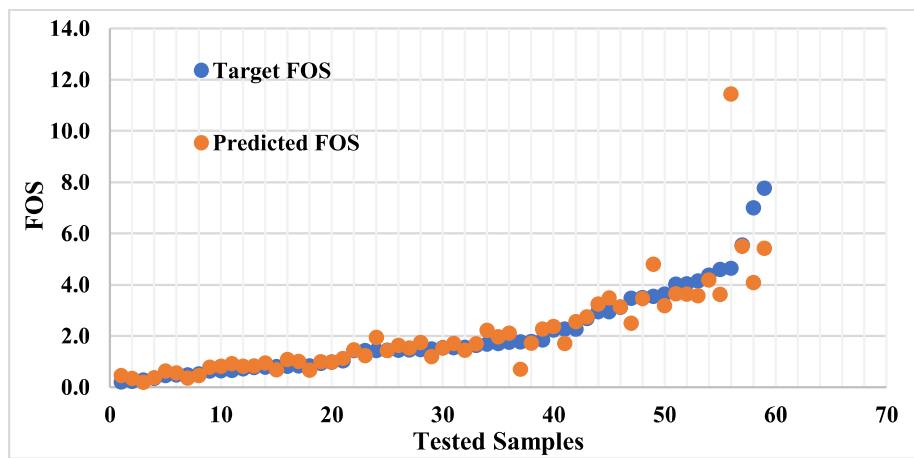


Fig. 6.6. Prediction of FOS for test data compared with the target FOS

Residual error for the training, testing and validation phase of the ANN1 model was calculated, and the error plot has been shown in Fig. 6.7. The deviation interval of the ANN1 model in the training phase ranges from -4.2 to 2.34, while for the testing phase, it ranges from -0.20 to 0.15 and for the validation phase, it ranges from -0.12 to 0.21. The decrease in residual error values from the training to validation phase represents the organic learning ability of the

neural networks where the outputs of the network are not limited entirely by inputs and results given to them initially by an expert system. ANN have the ability to generalise their inputs. This ability is valuable for robotics, pattern recognition and highly heterogenous systems. Also, the ANN have the potential for high fault tolerance. The output generation is not affected by the corruption of one or more cells of the artificial neural network resulting in an increase in prediction ability.

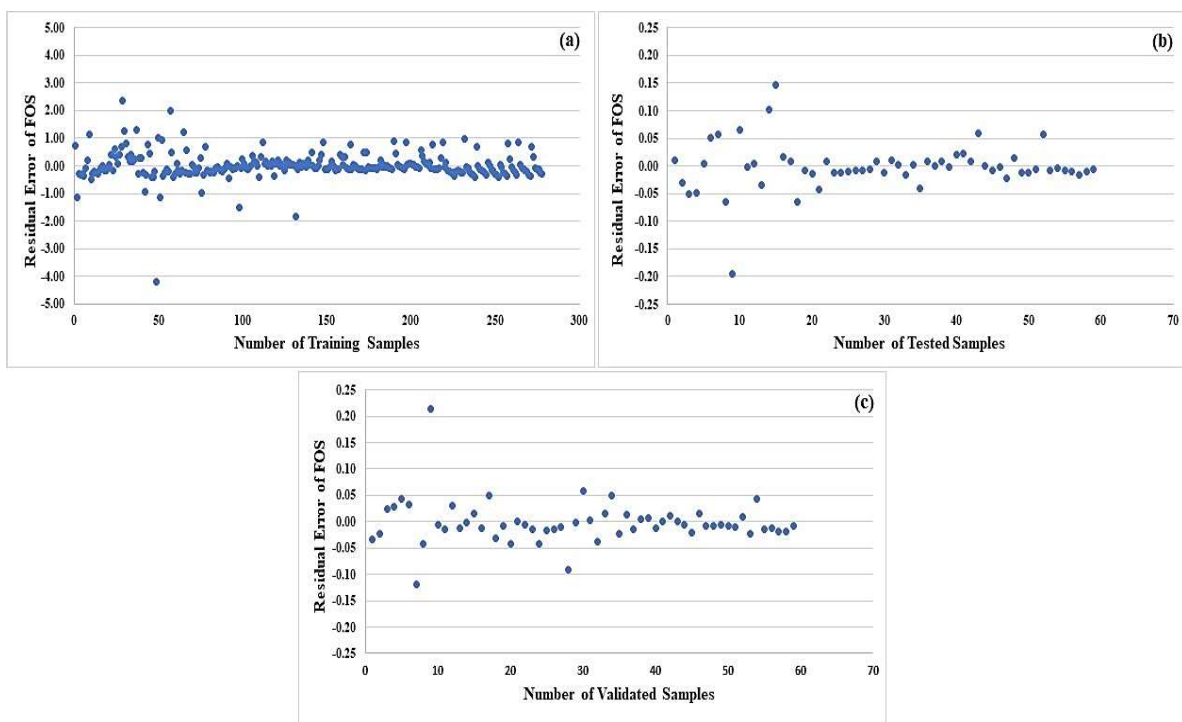


Fig. 6.7. Residual Error Plot of FOS for (a) Training samples, (b) Testing samples and (c) Validation samples in case of ANN1 model

6.3.1.1 Relative Importance of Input Parameters Based on ANN1 Model

Once the developed neural network has been trained, tested and validated, it is essential to identify the relative importance of all the input parameters on the output (FOS in this case). It will be helpful during landslide vulnerability assessment in giving special focus to the relatively more important slope geotechnical or physical parameter affecting the overall stability. The Garson

equation (Garson 1991), based on the neural network weight matrix depicted in Eqn. 6.7, was used to calculate the relative importance of the independent input parameters.

$$Q_i = \frac{\sum_{j=1}^n (|IW_{j,i}| / \sum_{i=1}^3 |IW_{j,i}|) |OW_{ji}|}{\sum_{i=1}^3 (\sum_{j=1}^n (|IW_{j,i}| / \sum_{i=1}^3 |IW_{j,i}|) |OW_{ji}|)} \quad (6.7)$$

Where i is the input variables, j is the neurons within the hidden layer, Q_i is the relative importance of the i^{th} input variable on the output or dependent variable, $OW_{j,i}$ is the weight of output variable for the j^{th} neuron, $IW_{j,i}$ is the weight of j^{th} neuron from the i^{th} input variable of hidden layer and n denotes the number of neurons. The connecting weights of output and input hidden layer connection for the best-selected network (MLP 8-12-1) for the ANN1 model are shown in Table 6.3.

Table 6.3: Connecting weights of the selected ANN1 model

Network (MLP 8-12-1)	α ($^\circ$)	H (m)	D (m)	Φ_s ($^\circ$)	Cs (kPa)	γ_s (kN/m 3)	Es (MPa)	Φ_{s-r} ($^\circ$)	FOS
Hidden neuron 1	-1.2218	-0.3687	-0.6813	-0.0487	0.6787	-0.1841	0.1627	-0.4242	-0.5238
Hidden neuron 2	0.1789	0.4680	0.2876	0.0154	0.0241	0.0223	0.0029	0.0357	-0.5896
Hidden neuron 3	0.7554	1.7615	3.0526	0.2669	0.6693	-1.0489	0.3120	1.1034	-3.6820
Hidden neuron 4	-0.7804	-0.4606	-0.0653	-0.3870	-0.4408	0.0451	-0.3425	0.1602	-4.2464
Hidden neuron 5	-4.0841	1.9918	-2.5470	0.0239	0.2425	-1.2217	0.2908	-0.3100	4.5522
Hidden neuron 6	3.1989	1.0848	-0.4782	0.1791	0.0208	0.5529	0.0551	0.4562	-1.2260
Hidden neuron 7	2.4177	0.2135	4.5019	1.6661	0.1920	1.5988	3.5436	0.2228	5.5513
Hidden neuron 8	-1.6028	-0.5122	0.1502	-0.4237	-0.0016	-0.0922	-0.1346	-0.1534	0.9212
Hidden neuron 9	-3.6004	2.1897	-2.3605	0.4961	0.4169	1.8589	0.6534	0.6119	0.0558
Hidden neuron 10	-6.8262	1.9042	-2.6096	-0.6864	-0.6082	-0.5389	0.7972	-0.9654	1.9501
Hidden neuron 11	-1.1423	-0.4405	-0.6000	-0.0470	0.7350	-0.0773	0.3286	-0.5518	-0.9268
Hidden neuron 12	-0.4051	-0.6332	0.5006	-0.2140	-0.2764	-0.4462	-0.2692	-0.1649	-0.7899

The relative importance analysis for the developed ANN1 model has been calculated using Eqn. 6.7 and presented in Table 6.4. The slope inclination angle has the maximum influence with a relative importance of 27.61% on the stability of the residual soil slope followed by soil depth (20.83%), slope height (14.42), soil young's modulus (9.99%), soil unit weight (8.14%), soil friction angle (6.86%) and soil cohesion (6.37%). While the soil rock interface friction angle has

the minimal importance of 5.78%. These results can be compared with the correlation analysis performed in Table 5.7. According to correlation analysis, slope angle has the maximum correlation with FOS followed by soil depth, slope height, soil young's modulus, soil unit weight, soil friction angle and soil rock interface friction angle. While soil cohesion has a minimal correlation factor. The rest other parameters have very less correlation factors. The results for both analyses are comparable. Therefore, it can be concluded that the developed ANN1 model is highly efficient in evaluating the vulnerability profile of the residual soil slope under normal disturbed conditions (natural moisture and fine content).

Table 6.4: Relative importance of input variables for the developed ANN1 model

Input Parameter	Garson's Algorithm		Correlation Analysis	
	Relative Importance (%)	Ranking	Correlation	Ranking
α ($^{\circ}$)	27.61	1	-0.73	1
H (m)	14.42	3	-0.32	3
D (m)	20.83	2	-0.43	2
Φ_s ($^{\circ}$)	6.86	6	0.18	6
Cs (kPa)	6.37	7	0.12	8
γ_s (kN/m ³)	8.14	5	0.20	5
Es (MPa)	9.99	4	0.24	4
Φ_{s-r} ($^{\circ}$)	5.78	8	0.13	7

6.3.2 ANN2 Model for Detail Landslide Hazard Identification

Nine significantly independent parameters (correlation coefficient > 0.1) were identified from the correlation analysis of seventeen independent slope physical and geotechnical parameters (Table 5.9). Numerical simulations of 6400 slope models (Section 5.3.2) were considered input parameters for the neural network. The selected nine input parameters are represented as the input layer, while the FOS is represented as the output layer in the developed ANN2 architecture. The most suitable neural network architecture was deduced by training, testing and validating different combinations of hidden layers and associated neurons. A single hidden layer having a range of 2–

15 neurons have been opted to train the neural network model. The normalising of the input data was performed, and the training process was initiated by randomly varying the number of neurons and their associated weights. The network with 9-11-1 architecture (nine neurons in the input layer, eleven neurons in a single hidden layer and one neuron in the output layer) is selected based on maximum training performance and minimum training error for the ANN2 model after simulation of various network combinations (Table 6.5). The selected ANN2 model has a learning rate and momentum of 0.94 and 0.012, respectively, and its architecture is shown in Fig. 6.8.

Table 6.5: Identification of best MLP for ANN2 during the training process

Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
MLP 9-6-1	0.991	0.991	0.980	0.030	0.024	0.027	BFGS 552	SOS	Exponential	Exponential
MLP 9-11-1	0.994	0.991	0.982	0.026	0.023	0.025	BFGS 147	SOS	Logistic	Exponential
MLP 9-9-1	0.990	0.982	0.978	0.033	0.025	0.030	BFGS 149	SOS	Exponential	Sine
MLP 9-4-1	0.894	0.902	0.980	0.346	0.308	0.290	BFGS 11	SOS	Identity	Logistic
MLP 9-13-1	0.992	0.991	0.989	0.024	0.029	0.027	BFGS 147	SOS	Tanh	Logistic
MLP 9-11-1	0.909	0.917	0.913	0.299	0.262	0.255	BFGS 10	SOS	Identity	Exponential
MLP 9-2-1	0.905	0.912	0.911	0.307	0.275	0.260	BFGS 27	SOS	Sine	Exponential
MLP 9-5-1	0.986	0.989	0.985	0.049	0.037	0.045	BFGS 75	SOS	Exponential	Identity
MLP 9-6-1	0.990	0.992	0.989	0.035	0.027	0.032	BFGS 378	SOS	Tanh	Sine
MLP 9-14-1	0.993	0.991	0.893	0.023	0.019	0.021	BFGS 253	SOS	Tanh	Sine
MLP 9-8-1	0.992	0.991	0.982	0.024	0.026	0.023	BFGS 124	SOS	Logistic	Tanh
MLP 9-3-1	0.964	0.964	0.959	0.121	0.117	0.122	BFGS 83	SOS	Exponential	Sine
MLP 9-6-1	0.993	0.990	0.990	0.025	0.022	0.023	BFGS 349	SOS	Exponential	Tanh
MLP 9-15-1	0.991	0.984	0.961	0.020	0.018	0.021	BFGS 173	SOS	Exponential	Identity
MLP 9-12-1	0.909	0.917	0.913	0.299	0.263	0.255	BFGS 11	SOS	Identity	Exponential

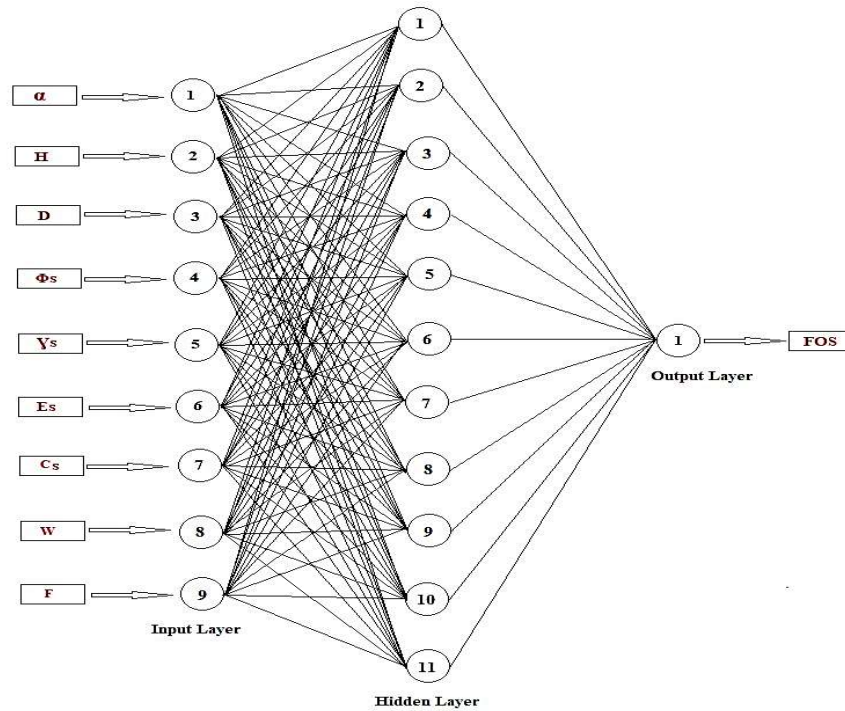


Fig. 6.8. Network architecture (MLP 9-11-1) of the developed ANN2 model

During the training process, the number of epochs (iterations) is gradually increased from 1 to 200 (Fig. 6.9). Repeated iteration is performed using the Levenberg–Marquardt backpropagation method until error is minimized to an acceptable value (Table 6.5). Based on the error analysis, the number of epochs was set to 194, and the minimum RMSE value of 0.00014 was achieved.



Fig. 6.9. Training RMSE curve of the selected MLP 9-11-1 for ANN2 model

Testing and validation have been performed after the network training phase is completed. The input parameters for various slope configurations are fed into the network for predicting the corresponding FOS. The predicted FOS are compared with the corresponding numerical simulation results for efficiency calculation. A comparison of FOS from the numerical simulation (Target FOS) with predicted from the ANN2 model (Output FOS) is depicted in Fig. 6.10 for the training, testing and validation phase.

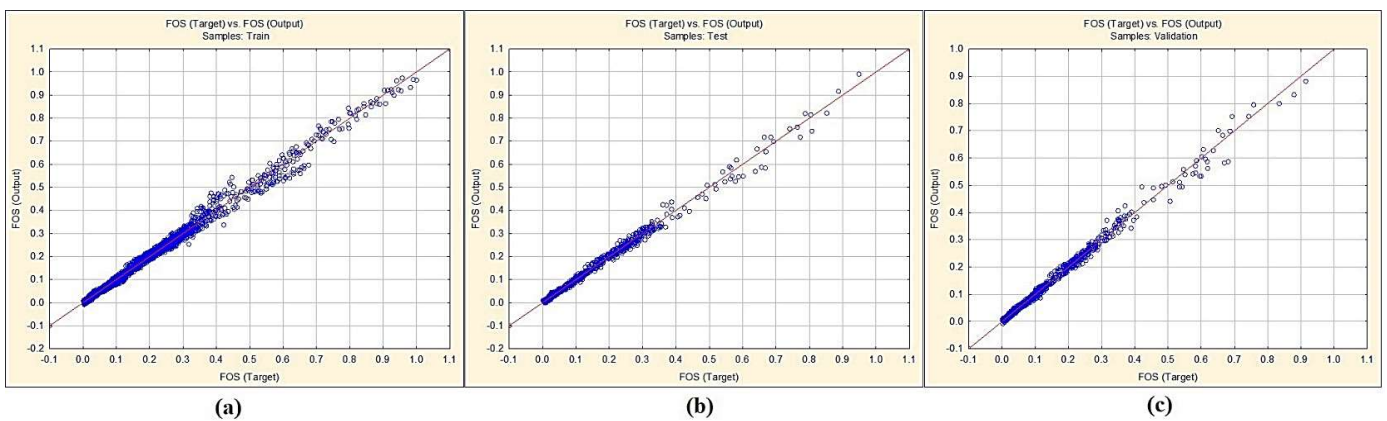


Fig. 6.10. Targeted and output FOS for the ANN2 model during training, testing, and validation phase

The coefficient of determination (R^2) between the target and predicted values indicates a good prediction performance of the model. The RMSE and VAF were computed for studying the performance and the prediction capacity of the developed predictive model. Various performance indices obtained from the developed ANN2 model is presented in Table 6.6. The learning rate curve of the selected MLP during the training and validation phase is shown in Fig. 6.11.

Table 6.6 Performance indices of the developed ANN2 model

Model	Data	R^2 (%)	RMSE	VAF (%)	Learning Rate
ANN2 (MLP 9-11-1)	Training Set	99.28	0.00014	99.22	0.96
	Testing Set	98.96	0.00116	98.47	0.93
	Validating Set	98.28	0.00184	97.26	0.92

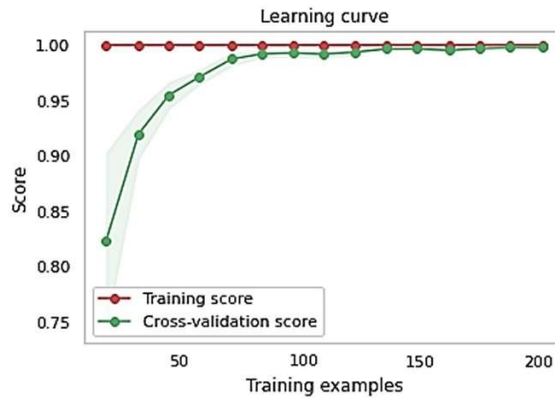


Fig. 6.11. Learning rate chart for training and validation phase of the developed ANN2 model

Fig. 6.12 depicts a comparison between the predicted FOS obtained from the ANN2 model with that of the target FOS obtained from the numerical simulation. It can be inferred that the prediction of the ANN2 model is relatively closer to the target values and within an acceptable level of confidence.

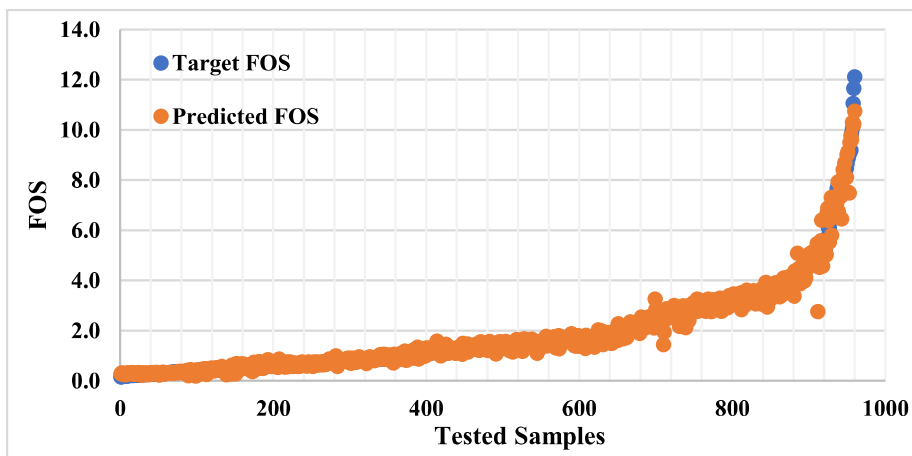


Fig. 6.12. Prediction of FOS for test data compared with the target FOS

Residual error for the training, testing and validation phase of the ANN2 model was calculated, and the error plot has been shown in Fig. 6.13. The deviation interval of the ANN2 model in the training phase ranges from -0.098 to 0.089, while for the testing phase, it ranges from -0.063 to 0.080 and for the validation phase, it ranges from -0.068 to 0.094. The decrease in residual error values from the training to validation phase represents the organic learning ability

of the neural networks where the outputs of the network are not limited entirely by inputs and results given to them initially by an expert system. ANN have the ability to generalise their inputs. This ability is valuable for robotics, pattern recognition and highly heterogeneous systems. Also, the ANN have the potential for high fault tolerance. The output generation is not affected by the corruption of one or more cells of the artificial neural network, increasing prediction ability.

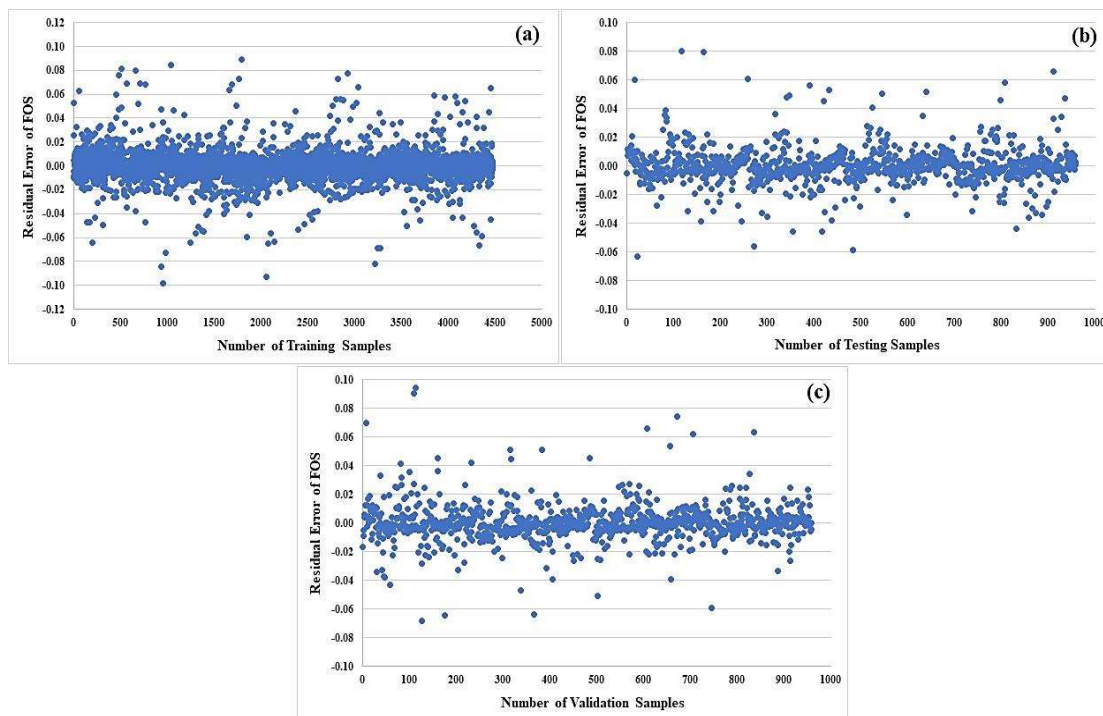


Fig. 6.13. Residual Error Plot of FOS for (a) Training samples, (b) Testing samples and (c) Validation samples in case of ANN2 model

6.3.2.1 Relative Importance of Input Parameters Based on ANN2 Model

Once the developed neural network has been trained, tested and validated, it is essential to identify the relative importance of all the input parameters on the output (FOS). It will be helpful during landslide vulnerability assessment in giving special focus to the relatively more important slope geotechnical or physical parameter affecting the overall stability. The Garson equation (Garson 1991), based on the neural network weight matrix depicted in Eqn. 6.7, was used to calculate the relative importance of the independent input parameters. The connecting weights of

output and input hidden layer connection for the best-selected network (MLP 9-11-1) for the residual soil slope model are shown in Table 6.7.

Table 6.7: Connecting weights of the selected ANN2 model

Network (MLP 9-11-1)	α ($^{\circ}$)	D (m)	F (%)	H (m)	W (%)	Cs (kPa)	Φ_s ($^{\circ}$)	Es (MPa)	γ_s (kN/m ³)	FOS
Hidden neuron 1	2.730	-5.357	-0.027	-1.510	-0.041	-0.062	0.070	-0.028	-0.015	-2.383
Hidden neuron 2	6.768	1.031	0.267	0.446	0.775	-0.079	-0.046	-0.009	-0.051	-3.508
Hidden neuron 3	2.716	0.285	-5.886	2.773	0.519	-0.727	0.689	0.045	0.684	0.264
Hidden neuron 4	1.134	0.810	-1.026	-0.145	2.332	0.189	0.197	0.004	0.129	-4.274
Hidden neuron 5	-27.974	0.955	-0.432	-2.792	2.116	0.050	0.181	0.271	0.184	-6.834
Hidden neuron 6	-4.552	0.388	0.851	-1.970	45.118	-1.656	2.971	5.602	1.143	5.525
Hidden neuron 7	-3.985	4.523	0.826	2.449	7.023	-0.044	0.099	0.251	-0.261	1.941
Hidden neuron 8	0.295	-0.360	4.750	2.228	13.845	0.780	1.093	-0.296	-0.364	0.282
Hidden neuron 9	-2.191	1.607	-1.265	7.975	1.632	0.032	-0.499	0.022	0.646	-0.735
Hidden neuron 10	1.192	1.229	0.647	1.235	-0.247	-0.178	-0.261	-0.038	-0.389	-2.965
Hidden neuron 11	-0.668	0.148	5.386	0.458	20.093	-1.320	0.819	-0.650	-0.153	-1.424

The relative importance analysis for the developed ANN2 model has been calculated using Eqn. 6.7 and presented in Table 6.8. The slope angle has the maximum influence with a relative importance of 36.7% on the stability of the residual soil slope followed by soil water content (27.6%), soil depth (12.3%), slope height (9.1%), percentage fines in soil (6.4%), soil friction angle (2.3%), young's modulus (2.1%) and soil unit weight (1.8%). While soil cohesion has the minimal importance of 1.7%. These results can be compared with the correlation analysis performed in Table 5.9. According to correlation analysis, slope angle has the maximum correlation with FOS followed by soil water content, soil depth, slope height, percentage fines in soil, soil friction angle, soil young's modulus and soil cohesion. While the soil unit weight has a minimal correlation factor. The rest other parameters have very less correlation factors. The results for both analyses are comparable. Therefore, it can be concluded that the developed ANN2 model is highly efficient in evaluating the vulnerability profile of the residual soil slope under varying moisture and fine content.

Table 6.8: Relative importance of input variables for the developed ANN2 model

Input Parameter	Garson's Algorithm		Correlation Analysis	
	Relative Importance (%)	Ranking	Correlation	Ranking
α ($^{\circ}$)	36.76	1	-0.63	1
D (m)	12.26	3	-0.33	3
F (%)	6.36	5	0.22	5
H (m)	9.09	4	-0.29	4
W (%)	27.57	2	-0.51	2
Cs (kPa)	1.73	9	0.14	8
Φs ($^{\circ}$)	2.35	6	0.18	6
Es (MPa)	2.09	7	0.16	7
Υs (kN/m³)	1.80	8	0.13	9

6.4 Discussion

Using the data from numerical analysis (previous chapter), two ANN models, namely ANN1 and ANN2, were developed, which corresponds to the quick and detailed landslide hazard identification, respectively. The ANN models can be used in conjunction with the proposed hazard chart for analysing the residual soil slope behaviour of Lesser Himalayan slopes (possessing calcareous lithologies). Several key performance indices like root mean square error, coefficient of determination, residual error, the variance accounted for and the learning rate is used for assessing the efficacy of the developed ANN models. The high efficiency of both the developed ANN models also proves the validity of the results obtained from numerical analysis performed in Chapter 5, which in turn proves the accuracy of the developed hazard charts.

Some of the key benefits of using ANN models include the ease of handling highly heterogeneous non-linear datasets. Since the input dataset is obtained from the 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. Another key benefit of using ANN models is the ease of updating the database. More datasets can be incorporated in future, which will further help in increasing the predicting ability of the models as observed in the case of higher prediction ability of the developed ANN2 model than the ANN1 model. The higher accuracy of the developed ANN2 model compared to the ANN1 model is due to the large size input data set during training.

It was observed that the error dispersion during training of the ANN2 network is much less compared to error dispersion during training of the ANN1. This may be due to the utilisation of a significant number of samples chosen for training (4480, i.e., 70% of 6400) compared to 280 (70% of 400) samples during ANN1 training. The use of a larger number of significant input parameters based on correlation analysis and scaling effect resulted in better performance of ANN2, which could be attributed to the sufficient amount of data in the solution space of ANN2. The developed ANN models were also used to obtain the relative importance of the input parameters based on Garson's Equation. The reducing order of the top five importance input variable according to ANN analysis is slope angle, water content, soil depth, slope height and percentage fines. The obtained order for relative importance is according to the correlation analysis performed in Chapter 5.

The current chapter and the previous chapter deal with the pre-failure slope stability analysis. Both the Landslide Hazard Chart and the ANN models are useful in identifying the current stability condition of the slope. This will help in taking remedial measures to mitigate the disaster or to avoid it. However, once the slope failure has occurred, a specific quantity of dislodged geomaterial, also known as debris, is produced, which moves downslope due to gravity. Debris flow is one of the severe outcomes of the landslide that needs a detailed investigation to achieve sustainable disaster risk reduction goals. The following chapter deals with landslide generated debris flow analysis in detail.