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Determination of Suitable Hyperparameters of Artificial Neural Network for the Best Prediction of Geotechnical Properties of Soil

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Abstract: The artificial neural network is robust in predicting soil properties. The present study aims to determine the suitable hyperparameters such as number of hidden layers, neurons, and backpropagation algorithms for the best prediction of geotechnical properties of soil. The supervised learning category-based multilayer perceptron artificial neural network approach is used, and models are developed in MATLAB R2020a. The ANN models are configured with neurons (5, 10 & 15), hidden layers (one to five), and a backpropagation algorithm (LM, BFG, SCG, GDA, GD & GDA). Fifteen ANN models are developed for each algorithm. The study shows that the LM, BFG, and SCG algorithm-based ANN models require strongly (0.61-0.8) to very strongly (0.81-1) correlated datasets. On the other hand, the GDM, GD, and GDA algorithm-based ANN models require only strongly correlated datasets to achieve a performance of more than 0.9. In most cases, it is also found that the GDM, GD, and GDA algorithm-based ANN models achieve high performance with three hidden layers interconnected with ten neurons. Still, LM algorithm-based ANN model achieves high performance with a single hidden layer interconnected with 5/15 neurons. The present work draws a relationship between the correlation coefficient and the number of hidden layers & neurons. It also helps to study the effect of hidden layers and neurons on the performance of ANN models. Formulas are derived from the performance of ANN models to calculate the required number of hidden layers and neurons for a particular backpropagation algorithm to achieve a testing performance of more than 0.9.

Keywords: Artificial Neural Network, Consistency Limits, Compaction Parameters, Hidden Layers, Backpropagation Algorithms

I. INTRODUCTION

Atterberg's limits and compaction parameters of soil play a vital role in any Civil Engineering Project. The liquid limit, plasticity index, and plastic limit are the Atterberg's limits of soil [4]. The liquid limit of soil is experimentally determined as per IS 2720 (P-5): 1985 [15] using Cone penetration and Casagrande tests apparatus. On the other hand, the compaction parameters are optimum moisture content and maximum dry density and are determined as per IS 2720 (P-7): 1980 [16] and IS 2720 (P-8): 1983 [17]. The compaction parameters are determined using a standard proctor and modified proctor test apparatus. The standard and modified proctor tests are light and heavy compaction tests. Analytical and laboratory methods can determine Atterberg's soil limits and compaction parameters of soil [28]. Regression analysis is the most popular statistical method used for prediction. The regression analysis predicts the compaction parameters for specific soils [10, 21, 23, 12, 8]. The published regression models predicted compaction parameters with a coefficient of determination ranging from 0.64 to 0.98. The prediction level of regression analysis is high for small datasets. The genetic programming-based multi expression programming approach predicts the OMC and MDD of soil with a coefficient of 0.923 and 0.858, respectively [27]. Optimum moisture content increases with the liquid limit of soil and is strongly related to each other. The plastic limit is directly related to OMC and MDD but not LL. Still, the best prediction of OMC and MDD can be achieved by both LL and PL [14, 26]. The regression analysis with SVM computes the OMC and MDD with a correlation coefficient of 0.92 and 0.89, respectively [11]. The maximum dry density decreases, and optimum moisture content increases with the plasticity index. Using the plasticity index, the prediction of OMC for a modified proctor is more than the standard proctor [20]. The GMDH-type neural network is a reliable AI approach for predicting OMC and MDD of soil [2]. The grain-size parameters of coarse soil play an important role in predicting the OMC and MDD of soil. The coefficient of uniformity and D30 can predict the MDD of soil with a prediction accuracy of ±2% [24]. Similarly, the coefficient of uniformity and D50 can predict the OMC of soil with a prediction accuracy of ±2% [10]. The empirical relationship helps to predict the compaction parameters of the modified proctor test using the compaction parameters of the standard proctor test.

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The artificial neural network has the potential to predict the OMC and MDD of soil [25]. The index properties, namely LL, PL, PI, FC, S, G, and SG, predict the OMC and MDD with high accuracy [19]. Multivariate adaptive regression splines predict compaction parameters with better performance than empirical equations, ANN and LSSVM. The sensitivity analysis shows that sand content and coefficient of uniformity highly affect compaction parameters' prediction [23]. The compaction parameters are highly influenced by Atterberg limits, clay content, silt content and electrical conductivity [22]. Soil parameters, namely LL, PL PI, SG, c, G, S, and FC, predict OMC and MDD with the correlation coefficient of 0.932 and 0.905, respectively [3].

The number of hidden neurons is based on the number of output neurons, input neurons, and training samples. Researchers suggested the following equations:

$$H = \frac{T - O}{I + O + 1} \quad (1)^{[1]}$$

$$H = 2 * I + 1 \quad (2)^{[9]}$$

$$H = \frac{I + O}{2} \quad (3)^{[7]}$$

$$H = 2 * I \quad (4)^{[5]}$$

$$H = \sqrt{I * O} \quad (5)^{[6]}$$

Where H, O, & I are the number of hidden neurons, output neurons & input neurons, and T is the training sample. The sand content affects the liquid limit of soil. Similarly, the plasticity index is affected by OMC, MDD, sand, and gravel content. Gaussian and Quadratic kernel-based support vector machine models predict soil's liquid limit and plasticity index with the performance of 0.9767 and 0.9828, respectively. [18]

II. DATA COLLECTION AND ANALYSIS

Data analysis is a process to study the datasets with the help of statistical tools or methods. The data analysis consists of details of data sources, descriptive statistics, frequency distribution, and correlation coefficient for pair of datasets, as discussed below.

A. Data Source

The soil datasets consist of sand content, fine content, liquid limit, plasticity index, optimum moisture content, and maximum dry density. A total of 356 datasets are collected from the published research work, as given in Table 1.

TABLE 1. DATA SOURCES

S. No.	Description	Quantity
1	Benson C. H. et al. (1994), "Estimating hydraulic conductivity of compacted clay liners."	67
2	Benson C. H. et al. (1995), "Hydraulic conductivity of thirteen compacted clays."	13
3	Najjar Y. M. et al. (1996), "Utilizing computational NN for evaluating the permeability of compacted clay liners."	47
4	Nagaraj H. B. et al. (2014), "Correlation of compaction characteristics of natural soils with modified plastic limit."	44
5	O. Gunaydin (2008), "Estimation of soil compaction parameters by using statistical analyses and ANNs."	126
6	NG. K. S. (2015), "Estimating maximum dry density and optimum moisture content of compacted soils."	09
7	Alim M. A. et al. (2021), "Prediction of compaction characteristics of soil using plastic limit."	10
8	Saikia Ankurjyoti et al. (2017), "Predicting compaction characteristics of fine-grained soils in terms of Atterberg limits."	40

The outliers & missing datasets are removed from collected datasets by pre-processing. After pre-processing, two hundred forty-three soil datasets were collected and divided into 190 training and 53 testing datasets. Furthermore, 190 training datasets are subdivided at 70% and 30% for the training and validation of models.

B. Descriptive Statistics

A dataset consists of many columns and rows; therefore, the descriptive statistics are mapped to study the dataset. The minimum, maximum, mean, mode, median, standard deviation, confidence level at 95%, etc., are parameters of descriptive statistics. In the present research work, the minimum, maximum, mean (average), standard deviation (St. Dev), and confidence interval (CL) at 95% is determined for each feature of the dataset. The descriptive statistics of 190 datasets are shown in Table 2.

TABLE 2. DESCRIPTIVE STATISTICS OF DATASETS

Parameters	S (%)	FG (%)	LL (%)	PL (%)	PI (%)	OMC (%)	MDD (gm/cc)
Minimum	3.02	25.65	21.34	4.63	13.74	9.00	1.44
Maximum	70.28	96.98	65.13	29.46	38.72	30.40	2.01
Mean	29.29	68.78	35.41	14.03	21.38	15.74	1.76
Kurtosis	-0.90	-0.83	-0.32	-0.46	0.23	0.43	0.04
Skewness	0.44	-0.42	0.73	0.32	1.05	0.95	-0.60
St. Dev.	17.29	18.08	10.40	5.28	5.64	4.33	0.12
CL (95%)	2.47	2.59	1.49	0.75	0.81	0.62	0.02

C. Pearson's Product-Moment Correlation Coefficient

The correlation coefficient is the way to determine the strength of the linear relationship between independent and dependent variables. The Linear or curvilinear correlation, scatter diagram method, Pearson's product-moment correlation coefficient, and spearman's rank correlation coefficient are the methods for determining correlation coefficient or relationship. The relationship of the pair of datasets according to the range of correlation coefficients is given in Table 3 [13].

TABLE 3 – LEVEL OF RELATIONSHIP VS VALUE OF CORRELATION COEFFICIENT

Correlation Coefficient	Level of Relationship
±0.81 to ±1.00	Very Strong/ Strongest
±0.61 to ±0.80	Strong
±0.41 to ±0.60	Moderate
±0.21 to ±0.40	Weak
±0.00 to ±0.20	No Relationship

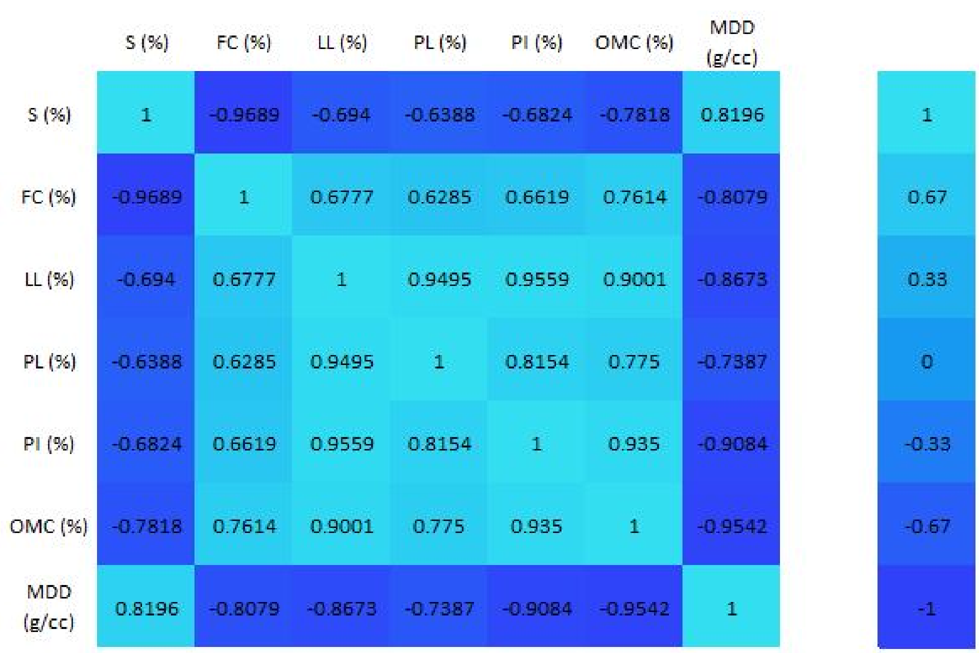
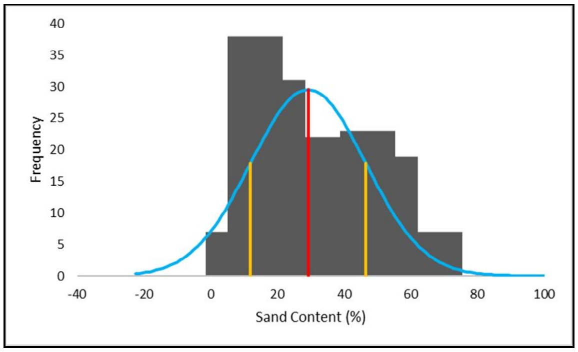


Fig. 1. Pearson's correlation coefficient for 190 soil datasets

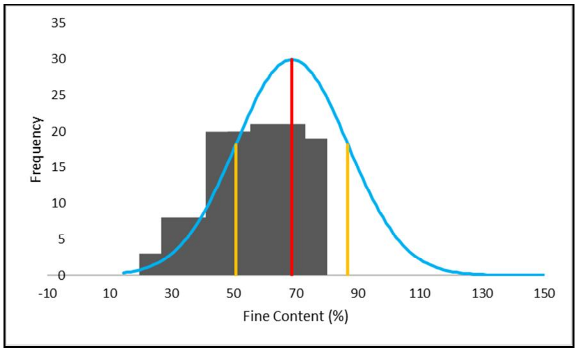
Fig. 1 depicts the Pearson's correlation coefficient for 190 training datasets. The consistency limits of soil are affected by the shape and size of particles. Therefore, the sand and fine content are input parameters to predict the liquid limit, plastic limit, and plasticity index. Thus, the compaction parameters of soil are affected by sand, fine content, and consistency limits. Therefore, the sand, fine content, LL, PL, and PI are used as input parameters to predict the OMC and MDD of soil. From Figure 2, the following points are observed; (i) the liquid limit, plastic limit, and plasticity index have a strong relationship with sand and fine content, (ii) the liquid limit and plasticity index have a very strong relationship with optimum moisture content, (iii) the sand content, liquid limit, and plasticity index has a very strong relationship with maximum dry density, (iv) the sand & fine content and plastic limit has a strong relationship with optimum moisture content, (v) the sand content and plastic limit has a strong relationship with maximum dry density, (vi) the sand & fine content, LL & PL, LL & PI, and PL & PI have multicollinearity.

D. Frequency Distribution

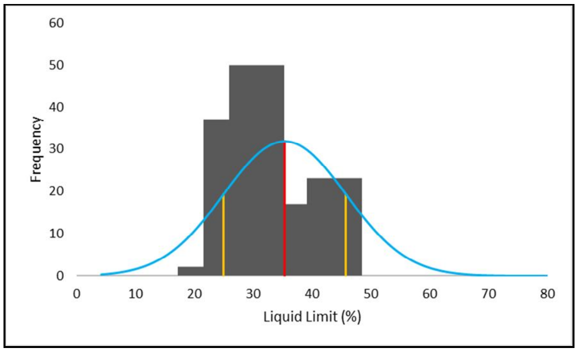
Frequency distribution (FD) is a graphical presentation of the number of observations for a specific interval. The histogram is a bar graph-like representation of the frequency of datasets. The frequency distribution of features of consistency limit with OMC & MDD is shown in Fig. 2.



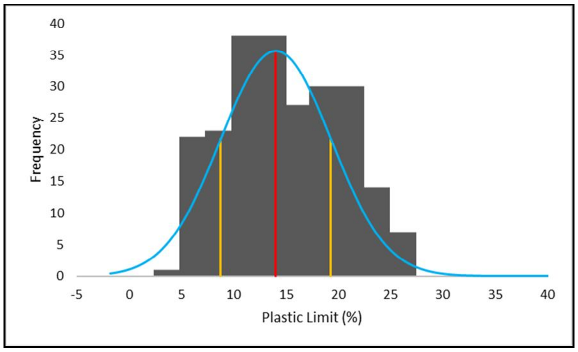
(a) FD of sand content



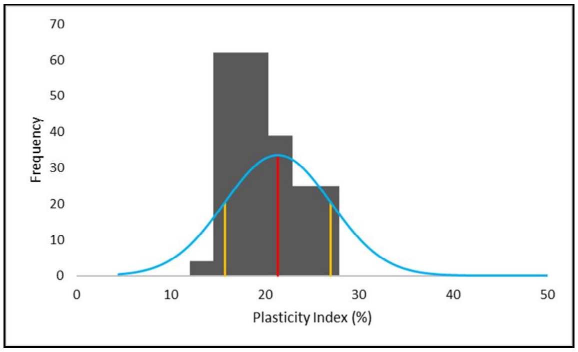
(b) FD of fine content



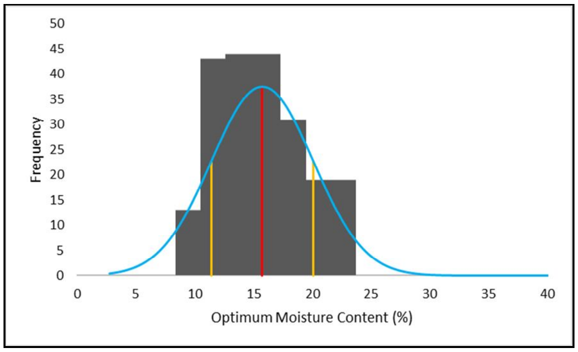
(c) FD of liquid limit



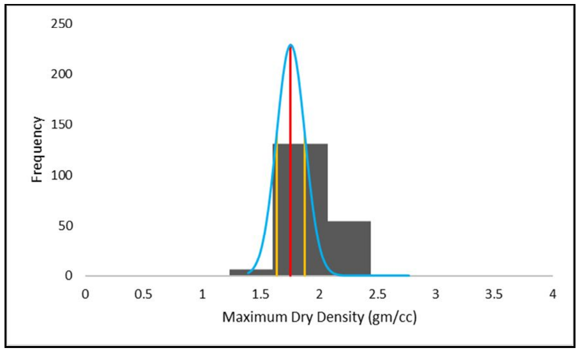
(d) FD of plastic limit



(e) FD of plasticity index



(f) FD of optimum moisture content



(g) FD of maximum dry density

Fig. 2. Frequency distribution of 190 soil dataset

III.METHODOLOGY

The present research work adopted the artificial neural network approach to predict soil's consistency limits and compaction parameters. An artificial neural network is an approach to deep learning, and deep learning is a subset of machine learning. The artificial neural network is a network of input, hidden & output layers and interconnected by neurons. The hidden layer and output layer has linear or nonlinear activation function to improve the performance of the ANN models. Each artificial neural network has a feedforward and backpropagation process. The information travels from the input to the output layer through hidden layer(s) in the feedforward process. Thus, the information travels from output to input layers in the backpropagation process. The backpropagation process is performed using different algorithms such as Levenberg Marquardt, BFGs Quasi-Newton, Scaled Conjugate Gradient, Gradient Descent with Momentum, Gradient Descent, and Gradient Descent with Adaptive Learning. The mathematical expression of the backpropagation algorithm is given below.

Levenberg Marquardt Algorithm –

$$[J^T J + \lambda diag(J^T J)]\,\delta = J^T[y - f(\beta)] \tag{6}$$

BFGs Quasi-Newton Method –

$$B_{k+1}^{-1} = B_k^{-1} + \frac{(s_k^T y_k + y_k^T B_k^{-1} y_k)(s_k s_k^T)}{(s_k^T y_k)^2} - \frac{B_k^{-1} y_k s_k^T + s_k y_k^T B_k^{-1}}{s_k^T y_k} \tag{7}$$

Scaled Conjugate Gradient –

$$f(x_{k+1}) = f(x_k) - \left[\frac{(a_k + (b_k + 2\alpha_k s_k))^2}{2(b_k + 2\alpha_k s_k)} - \rho\alpha_k\right] \le f(x_k) \tag{8}$$

Gradient Descent with Momentum –

$$w_i'(t) = c_1 e^{\lambda i,1t} + c_2 e^{\lambda i,2t} \tag{9}$$

Gradient Descent –

$$w := w - \eta \nabla Q_i(w) \tag{10}$$

Gradient Descent with Adaptive Learning –

$$w_j := w_j \frac{\eta}{\sqrt{G_{i,j}}} g_j \tag{11}$$

In the present research work, the multilayer perceptron artificial neural network has been developed to predict soil's LL, PI, OMC, and MDD. The developed artificial neural network is configured with different parameters, as given in Table 4.

TABLE 4. CONFIGURATION OF ARTIFICIAL NEURAL NETWORKS

Hyperparameters	Status
Activation Function(s)	Linear at the output layer, Sigmoid at hidden layer(s)
Backpropagation Algorithm(s)	LM, BFG, SCG, GDM, GD, GDM
Neuron(s)	5, 10, 15
Hidden Layer(s)	1 to 5
Training: Validation Data Ratio	70: 30
Type of Network	Feed-forward backpropagation
Class of Network	Multilayer perceptron class
Epochs	1000
Minimum Gradient	10e-7
Maximum Failure	6
Mu	0.001

TABLE 5. ARTIFICIAL NEURAL NETWORK MODELS ID

Algorithm(s)	LL Models	PI Models	OMC Models	MDD Models
Levenberg Marquardt	Model 1 – 15	Model 101 – 115	Model 201 – 215	Model 301 – 315
BFGs Quasi-Newton	Model 16 – 30	Model 116 – 130	Model 216 – 230	Model 316 – 330
Scaled Conjugate Gradient	Model 31 – 45	Model 131 – 145	Model 231 – 245	Model 331 – 345
Gradient Descent with Momentum	Model 46 – 60	Model 146 – 160	Model 246 – 260	Model 346 – 360
Gradient Descent	Model 61 – 75	Model 161 – 175	Model 261 – 275	Model 361 – 375
Gradient Descent with Adaptive Learning	Model 76 - 90	Model 176 – 190	Model 276 – 290	Model 376 – 390

In the present research, fifteen ANN models are developed for each backpropagation algorithm to predict soil's LL, PI, OMC, and MDD. Ninety ANN models are used to predict each LL, PI, OMC, and MDD of soil. The details of the developed models are given in Table 5. Five, ten and fifteen neurons are employed for each one, two, three, four, and five hidden layers ANN model in every backpropagation algorithm ANN model. Therefore, fifteen ANN models are developed for each algorithm.

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IV. RESULTS AND DISCUSSIONS

In this section, the performance of developed artificial neural network models has been compared and discussed.

A. *Prediction of Liquid Limit*

For the prediction of liquid limit, the LM, BFG, SCG, GDA, GD, and GDM algorithm-based artificial neural network models have evolved with different numbers of hidden layers and neurons. The performance of the proposed models has been discussed below.

1) *Using Levenberg – Marquardt (LM) Algorithm Based Neural Network Models*

Fifteen LM algorithm-based ANN models have been developed for predicting the liquid limit of soil, and the performance of models is given in Table 6.

TABLE 6. PERFORMANCE OF LM ALGORITHM-BASED ANN MODELS FOR LIQUID LIMIT

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 1	1/5	0.0348	0.9926	0.0062	0.0404	0.9868	0.0076	7.6779	0.8335	5.3166
Model 2	1/10	0.0290	0.9946	0.0047	0.0476	0.9846	0.0070	6.7837	0.8215	4.2649
Model 3	1/15	0.0357	0.9916	0.1019	0.0413	0.9894	0.0852	5.4098	0.9165	4.6054
Model 4	2/5	0.0336	0.9925	0.0142	0.0395	0.9898	0.0144	5.8398	0.8918	4.8914
Model 5	2/10	0.0288	0.9950	0.0741	0.0456	0.9834	0.0601	5.0674	0.8893	3.9810
Model 6	2/15	0.0306	0.9944	0.0606	0.0454	0.9829	0.0659	7.2933	0.8383	4.7618
Model 7	3/5	0.0384	0.9923	0.0895	0.0495	0.9843	0.0880	7.1166	0.8652	5.3651
Model 8	3/10	0.0326	0.9926	0.1074	0.0390	0.9913	0.1136	6.4175	0.8847	5.0972
Model 9	3/15	0.0220	0.9970	0.0346	0.0768	0.9601	0.0396	7.1030	0.8152	5.7972
Model 10	4/5	0.0374	0.9903	0.0219	0.0421	0.9891	0.0239	4.8676	0.8921	4.1087
Model 11	4/10	0.0244	0.9959	0.0338	0.0426	0.9890	0.0363	6.8719	0.8752	5.5588
Model 12	4/15	0.0290	0.9949	0.1417	0.0444	0.9835	0.1340	5.7585	0.8761	4.1914
Model 13	5/5	0.0367	0.9910	0.0254	0.0416	0.9883	0.0239	4.8230	0.8918	4.0797
Model 14	5/10	0.0340	0.9926	0.0561	0.0481	0.9856	0.0534	4.9198	0.8960	4.0891
Model 15	5/15	0.0250	0.9962	0.1485	0.0459	0.9847	0.1574	5.2251	0.9017	4.1992

Table 6 shows that Model 3 predicts the liquid limit of soil with a performance of 0.9165. It has also been observed that the model's performance has been increased with neurons in the case of single hidden layer ANN models. The performance of two and four hidden layer-based ANN models has been decreased with neurons. On the other hand, the performance of three and five hidden layer-based ANN models has been increased with neurons. Models 8 and 9 performed well during training and validation, respectively, but Model 3 outperformed the other models while testing the model. Therefore, Model 3 has been identified as a better performance model for predicting soil LL.

2) *Using BFGs Quasi – Newton (BFG) Algorithm Based Neural Network Models*

The artificial neural networks have been developed to predict soil LL using BFG's Quasi-Newton algorithm. The performance of BFG algorithm-based models is given in Table 7.

TABLE 7. PERFORMANCE OF BFG ALGORITHM-BASED ANN MODELS FOR LIQUID LIMIT

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 16	1/5	0.0433	0.9875	0.0109	0.0532	0.9813	0.0128	3.8744	0.9299	3.5130
Model 17	1/10	0.0456	0.9866	0.0315	0.0419	0.9870	0.0386	3.8882	0.9357	3.1890
Model 18	1/15	0.0432	0.9883	0.0419	0.0406	0.9871	0.0347	4.2482	0.9276	3.7690
Model 19	2/5	0.0417	0.9883	0.0273	0.0486	0.9855	0.0280	5.5309	0.8699	4.0059
Model 20	2/10	0.0502	0.9841	0.0119	0.0533	0.9781	0.0134	5.8281	0.8831	4.6247
Model 21	2/15	0.0383	0.9907	0.0203	0.0531	0.9781	0.0237	6.4305	0.8855	5.2717

Model 22	3/5	0.0398	0.9893	0.0181	0.0454	0.9873	0.0192	3.4276	0.9308	2.9363
Model 23	3/10	0.0446	0.9873	0.0080	0.0471	0.9834	0.0090	4.3374	0.9297	3.7449
Model 24	3/15	0.0377	0.9911	0.0221	0.0475	0.9797	0.0236	4.2796	0.9069	3.4598
Model 25	4/5	0.0403	0.9883	0.0102	0.0461	0.9886	0.0148	3.9772	0.9193	3.4726
Model 26	4/10	0.0390	0.9892	0.0127	0.0527	0.9827	0.0126	5.9972	0.8204	5.3720
Model 27	4/15	0.0382	0.9895	0.0090	0.0373	0.9918	0.0088	4.6284	0.9134	4.0795
Model 28	5/5	0.0685	0.9699	0.0791	0.0794	0.9561	0.0894	4.1097	0.9457	3.1986
Model 29	5/10	0.0421	0.9868	0.0092	0.0535	0.9849	0.0104	4.6109	0.8960	3.7973
Model 30	5/15	0.0424	0.9886	0.0463	0.0461	0.9832	0.0441	4.2450	0.8962	3.5510

Table 7 shows the training, validation, and testing performance of BFG algorithm-based ANN models while predicting soil LL. The maximum performance of a single hidden layer-based ANN model has been achieved by providing ten neurons. Similarly, 0.8855 performance has been achieved by two hidden layer-based ANN models interconnected with 15 neurons. It has also been observed that the performance of BFG algorithm-based ANN models has been decreased by providing two hidden layers. Furthermore, the performance has been increased to 0.9308 by providing three hidden layers interconnected with five neurons. The performance of the BFG algorithm-based ANN model has been decreased for four hidden layers interconnected with ten neurons. The maximum performance has been obtained by the ANN model configured with five hidden layers and neurons, i.e., 0.9457. The performance results show that the two and four hidden layers-based BFG algorithm ANN models are less efficient in predicting soil LL.

3) Using Scaled Conjugate Gradient (SCG) Algorithm Based Neural Network Models

The artificial neural networks have been developed to predict the LL of soil using the Scaled Conjugate Gradient algorithm. The performance of SCG algorithm-based models is given in Table 8.

TABLE 8. PERFORMANCE OF SCG ALGORITHM-BASED ANN MODELS FOR LIQUID LIMIT

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 31	1/5	0.0400	0.9895	0.0091	0.0391	0.9896	0.0086	5.8712	0.8580	4.4288
Model 32	1/10	0.0783	0.9543	0.0314	0.0666	0.9758	0.0245	10.9706	0.6530	6.2406
Model 33	1/15	0.0357	0.9913	0.0135	0.0529	0.9827	0.0177	3.9087	0.9139	3.2967
Model 34	2/5	0.0462	0.9860	0.0145	0.0436	0.9875	0.0138	6.5925	0.7865	4.4876
Model 35	2/10	0.0441	0.9876	0.0345	0.0542	0.9779	0.0309	5.5497	0.8996	4.7476
Model 36	2/15	0.0794	0.9550	0.0139	0.0723	0.9681	0.0133	7.4810	0.9081	5.0158
Model 37	3/5	0.0714	0.9681	0.0197	0.0618	0.9712	0.0163	7.0896	0.8015	4.7810
Model 38	3/10	0.0426	0.9870	0.0065	0.0442	0.9896	0.0080	4.1566	0.9289	3.4511
Model 39	3/15	0.0772	0.9626	0.0390	0.0833	0.9494	0.0369	5.5827	0.8534	3.7674
Model 40	4/5	0.0473	0.9844	0.0142	0.0486	0.9858	0.0159	5.8853	0.9274	5.1693
Model 41	4/10	0.0507	0.9829	0.0610	0.0588	0.9759	0.0599	6.7630	0.8197	4.9343
Model 42	4/15	0.0692	0.9673	0.0436	0.0766	0.9636	0.0449	3.5280	0.9177	2.9274
Model 43	5/5	0.0467	0.9863	0.0345	0.0536	0.9758	0.0354	3.8318	0.9245	2.9846
Model 44	5/10	0.0506	0.9839	0.0155	0.0769	0.9540	0.0216	4.1485	0.8848	3.3674
Model 45	5/15	0.0496	0.9841	0.0186	0.0626	0.9717	0.0209	4.2353	0.9540	3.7518

From Table 8, it has been observed that the single, two, three, four, and five hidden layers SCG algorithm-based ANN models have predicted liquid limits with the performance of 0.9139, 0.9081, 0.9289, 0.9274, and 0.9540, respectively. Furthermore, the five hidden layers interconnected with 15 neuron-based ANN models outperformed the other SCG algorithm-based ANN models in predicting the liquid limit of soil with a performance of 0.9540.

4) Using Gradient Descent with Momentum (GDM) Algorithm Based Neural Network Models

The artificial neural networks have been developed to predict soil LL using Gradient Descent with Momentum algorithm. The performance of GDM algorithm-based models is given in Table 9.

TABLE 9. PERFORMANCE OF GDM ALGORITHM-BASED ANN MODELS FOR LIQUID LIMIT

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 46	1/5	0.0800	0.9586	0.0209	0.0767	0.9576	0.0185	5.9647	0.8322	4.9968
Model 47	1/10	0.1451	0.8575	0.0483	0.1815	0.8796	0.0753	12.9322	0.9122	8.4343
Model 48	1/15	0.1153	0.9103	0.0463	0.1344	0.9041	0.0558	5.6091	0.7938	4.2729
Model 49	2/5	0.1295	0.8816	0.0574	0.1373	0.8749	0.0527	5.3103	0.8867	4.3979
Model 50	2/10	0.2844	0.3751	0.6033	0.2681	0.2900	0.6413	7.8988	0.5598	5.4421
Model 51	2/15	0.0841	0.9541	0.0195	0.0931	0.9357	0.0197	6.8683	0.8607	5.1926
Model 52	3/5	0.1236	0.8817	0.0340	0.1537	0.8535	0.0485	6.6096	0.7355	5.1476
Model 53	3/10	0.1015	0.9297	0.0203	0.1110	0.9146	0.0298	4.7812	0.9618	3.0514
Model 54	3/15	0.3214	0.5528	0.1713	0.3283	0.5355	0.1483	10.7639	0.5848	7.4079
Model 55	4/5	0.1005	0.9297	0.0566	0.0999	0.9380	0.0602	6.0067	0.7397	4.5894
Model 56	4/10	0.1124	0.9080	0.0281	0.1291	0.9040	0.0359	3.7282	0.9144	2.6420
Model 57	4/15	0.0691	0.9671	0.0094	0.0764	0.9621	0.0093	2.9164	0.9325	2.0099
Model 58	5/5	0.1368	0.8732	0.0437	0.1199	0.8937	0.0335	3.1886	0.9426	2.1772
Model 59	5/10	0.0906	0.9441	0.0115	0.0922	0.9418	0.0107	6.9505	0.7866	4.9439
Model 60	5/15	0.1315	0.8746	0.0310	0.1349	0.8779	0.0333	3.9079	0.9513	2.7793

From Table 9, it has been observed that the one, two, three, four, and five hidden layers-based ANN models have predicted LL of soil with the performance of 0.9122, 0.8867, 0.9618, 0.9325, and 0.9513, respectively. Furthermore, the three hidden layers interconnected with ten neuron-based ANN models outperformed the other GDM algorithm-based ANN models in predicting the liquid limit of soil with a performance of 0.9618.

5) Using Gradient Descent (GD) Algorithm Based Neural Network Models

The artificial neural networks have been developed to predict the LL of soil using the Gradient Descent algorithm. The performance of GD algorithm-based models is given in Table 10.

TABLE 10. PERFORMANCE OF GD ALGORITHM-BASED ANN MODELS FOR LIQUID LIMIT

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 61	1/5	0.2067	0.7202	0.0604	0.2225	0.7351	0.0670	5.4149	0.7281	4.1979
Model 62	1/10	0.1273	0.8951	0.0323	0.1702	0.8292	0.0503	4.9193	0.9094	3.5267
Model 63	1/15	0.1092	0.9097	0.0540	0.1087	0.9401	0.0492	4.4827	0.8242	3.6448
Model 64	2/5	0.1017	0.9317	0.0213	0.1102	0.9045	0.0235	8.1135	0.7702	5.3699
Model 65	2/10	0.1327	0.8805	0.0303	0.1228	0.8996	0.0306	4.6994	0.8721	3.0587
Model 66	2/15	0.1244	0.8863	0.0468	0.1498	0.8539	0.0617	4.7975	0.8578	3.6794
Model 67	3/5	0.2447	0.4376	0.0679	0.2472	0.4964	0.0712	5.8200	0.7148	3.6111
Model 68	3/10	0.0782	0.9586	0.0086	0.0797	0.9575	0.0081	5.1040	0.9114	3.9607
Model 69	3/15	0.0873	0.9431	0.0401	0.0999	0.9522	0.0431	3.4436	0.9310	2.3775
Model 70	4/5	0.1324	0.8709	0.0443	0.1290	0.8985	0.0408	4.9713	0.8178	2.8388
Model 71	4/10	0.1221	0.8938	0.0324	0.0995	0.9393	0.0253	6.9482	0.6125	4.1104
Model 72	4/15	0.0787	0.9576	0.0180	0.0956	0.9429	0.0209	8.1832	0.8020	5.8414
Model 73	5/5	0.1340	0.8823	0.0521	0.1632	0.7879	0.0507	5.7355	0.7452	4.4033
Model 74	5/10	0.1009	0.9234	0.0256	0.1323	0.9214	0.0340	5.3225	0.8715	3.1104
Model 75	5/15	0.0765	0.9610	0.0120	0.0709	0.9647	0.0109	6.2058	0.8797	4.4540

From Table 10, it has been observed that the one, two, three, four, and five hidden layers-based ANN models have predicted LL of soil with the performance of 0.9094, 0.8721, 0.9310, 0.8020, and 0.8797, respectively. Furthermore, the three hidden layers interconnected with 15 neuron-based ANN models outperformed the other GD algorithm-based ANN models in predicting the liquid limit of soil with a performance of 0.9310.

6) Using Gradient Descent Algorithm with Adaptive Learning (GDA) Based Neural Network Models

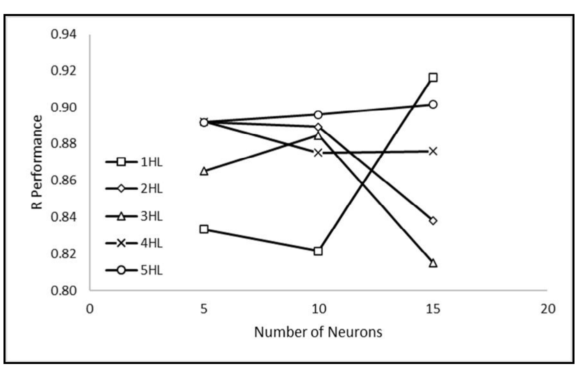
The artificial neural networks have been developed to predict soil LL using Gradient Descent with Adaptive Learning algorithm. The performance of GDA algorithm-based models is given in Table 11.

TABLE 11. PERFORMANCE OF GDA ALGORITHM-BASED ANN MODELS FOR LIQUID LIMIT

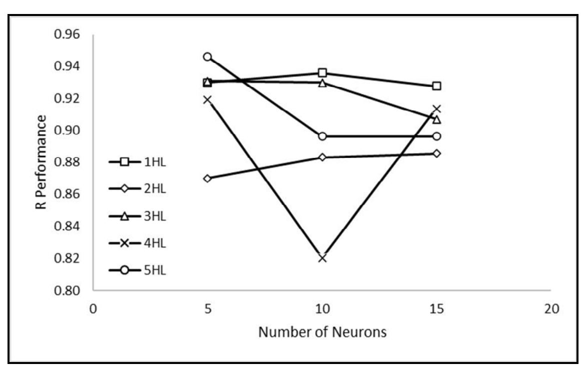
Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 76	1/5	0.0557	0.9810	0.0371	0.0633	0.9738	0.0329	3.5727	0.9223	2.6436
Model 77	1/10	0.0577	0.9796	0.0833	0.0697	0.9623	0.0799	4.5591	0.8907	3.7521
Model 78	1/15	0.0899	0.9476	0.2601	0.0968	0.9475	0.2806	5.2858	0.7781	2.9657
Model 79	2/5	0.0786	0.9599	0.0295	0.0894	0.9438	0.0248	4.1132	0.8749	3.0876
Model 80	2/10	0.0736	0.9643	0.0435	0.0795	0.9620	0.0533	4.5348	0.9004	3.1185
Model 81	2/15	0.0605	0.9766	0.0206	0.0839	0.9510	0.0235	3.8797	0.9330	2.4621
Model 82	3/5	0.0651	0.9739	0.0287	0.0670	0.9684	0.0271	9.0092	0.7800	5.9406
Model 83	3/10	0.1104	0.9192	0.0369	0.1046	0.9134	0.0343	2.2460	0.9634	1.5806
Model 84	3/15	0.0843	0.9528	0.0355	0.0880	0.9498	0.0398	5.6771	0.7517	3.5682
Model 85	4/5	0.1366	0.8693	0.0434	0.1165	0.9088	0.0420	4.6920	0.8651	3.0160
Model 86	4/10	0.0847	0.9496	0.0204	0.0954	0.9403	0.0202	7.4531	0.7947	4.4989
Model 87	4/15	0.0852	0.9523	0.0457	0.0792	0.9579	0.0429	6.9996	0.8408	4.6421
Model 88	5/5	0.1474	0.8491	0.0686	0.1334	0.8698	0.0582	3.9976	0.8997	2.6500
Model 89	5/10	0.1032	0.9311	0.0655	0.1194	0.8935	0.0621	4.1983	0.8881	2.9911
Model 90	5/15	0.0963	0.9331	0.1603	0.1111	0.9206	0.1588	6.6625	0.8391	4.3994

From Table 11, it has been observed that the one, two, three, four, and five hidden layers-based ANN models have predicted LL of soil with the performance of 0.9223, 0.9330, 0.9634, 0.8651, and 0.8997, respectively. In addition, the three hidden layers interconnected with ten neuron-based ANN models outperformed the other GDA algorithm-based ANN models in predicting the liquid limit of soil with a performance of 0.9634.

The performance variation of ANN models configured with different backpropagation algorithms for predicting the liquid limit of soil has been mapped, as shown in Fig. 3.



(a) Performance variation of ANN models configured with LM



(b) Performance variation of ANN models configured with BFG

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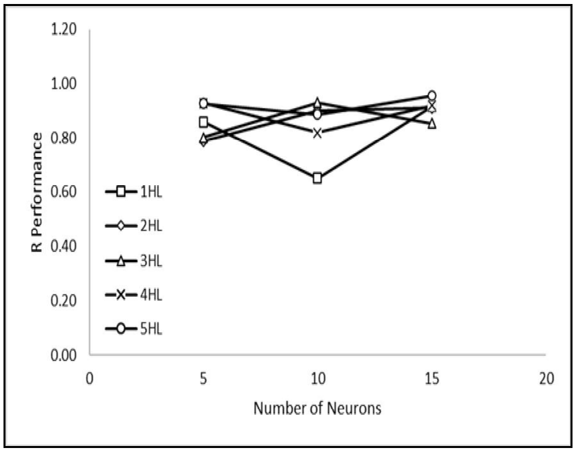
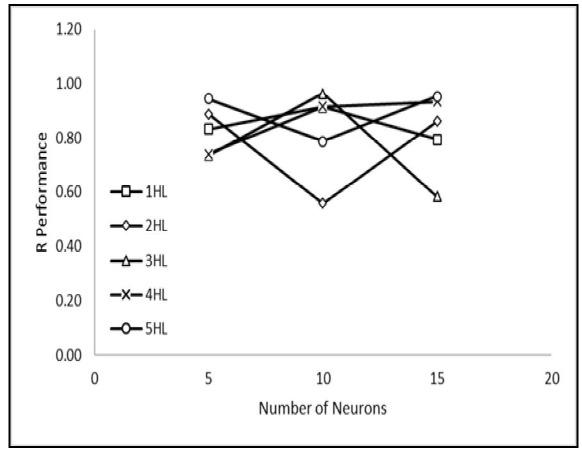
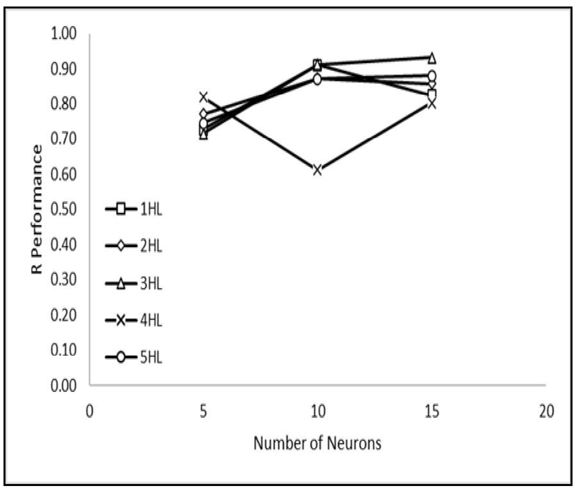


(c) Performance variation of ANN models configured with SCG

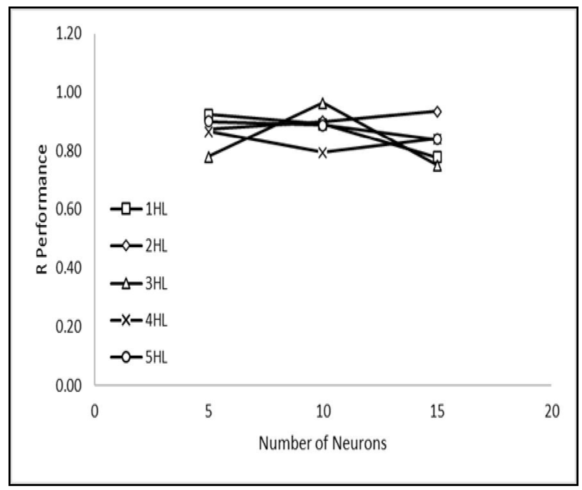


(d) Performance variation of ANN models configured with GDM

Fig. 3. Performance variation of ANN models in predicting liquid limit of soil (Conti…)



(e) Performance variation of ANN models configured with GD



(f) Performance variation of ANN models configured with GDA

Fig. 3. Performance variation of ANN models in predicting liquid limit of soil

Figure 3 depicts the performance variation of the ANN models configured with different backpropagation algorithms in predicting the liquid limit of soil. From figure 3, it has been observed that the ten neurons are a transition point because the performance of models has been increased/ decreased for five and fifteen neurons in predicting the liquid limit of soil. LM, BFG, and SCG algorithm-based ANN models predict the LL liquid limit of soil with a performance of more than 0.9 with single hidden layers interconnected with 5/15 neurons which are highly acceptable. Two and four hidden layers interconnected with 5/15 neurons also achieve high performance and accuracy in predicting soil LL.

B. Prediction of Plasticity Index

For the prediction of plasticity index, the LM, BFG, SCG, GDA, GD, and GDM algorithm-based artificial neural network models have been evolved with a different number of hidden layers and neurons. The performance of the proposed models has been discussed below.

1) Using Levenberg – Marquardt (LM) Algorithm Based Neural Network Models

Artificial neural networks have been developed to predict the PI of soil using the Levenberg-Marquardt algorithm. The performance of LM algorithm-based models is given in Table 12.

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TABLE 12. PERFORMANCE OF LM ALGORITHM-BASED ANN MODELS FOR PLASTICITY INDEX

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 101	1/5	0.0799	0.9770	0.1035	0.0912	0.9705	0.0966	5.5340	0.6820	4.5076
Model 102	1/10	0.0839	0.9750	0.1241	0.0944	0.9659	0.1304	5.4425	0.7205	4.5462
Model 103	1/15	0.0583	0.9880	0.0873	0.1286	0.9427	0.0828	6.3183	0.6548	5.1714
Model 104	2/5	0.0825	0.9760	0.3336	0.0793	0.9747	0.2922	4.7786	0.7280	3.8122
Model 105	2/10	0.0784	0.9780	0.1635	0.0763	0.9812	0.1725	5.5471	0.6723	4.6031
Model 106	2/15	0.1039	0.9639	0.1117	0.1202	0.9465	0.1319	3.8893	0.8040	2.9756
Model 107	3/5	0.0637	0.9859	0.0636	0.1017	0.9617	0.6085	4.4313	0.7235	3.4384
Model 108	3/10	0.0722	0.9818	0.0523	0.0867	0.9691	0.0505	5.6716	0.6762	4.3043
Model 109	3/15	0.0609	0.9864	0.0922	0.0948	0.9668	0.0906	5.4437	0.6755	4.1551
Model 110	4/5	0.0647	0.9852	0.0940	0.0976	0.9627	0.1114	4.5131	0.7141	3.6722
Model 111	4/10	0.0739	0.9822	0.0601	0.1085	0.9556	0.0608	5.8621	0.5043	4.4188
Model 112	4/15	0.0819	0.9756	0.0660	0.1272	0.9615	0.0774	5.2393	0.6113	4.1574
Model 113	5/5	0.0776	0.9778	0.0919	0.1061	0.9652	0.0983	4.1764	0.7452	3.2607
Model 114	5/10	0.1160	0.9607	0.0653	0.0990	0.9637	0.0617	4.8778	0.6843	3.8869
Model 115	5/15	0.0655	0.9840	0.0645	0.1140	0.9569	0.0600	5.8719	0.6147	4.5207

From Table 12, it has been observed that the LM algorithm-based ANN model predicted the plasticity index of soil with a performance of 0.8040. However, it has also been observed that LM algorithm-based ANN models have not predicted PI with a performance of more than 0.90 because of the relationship between sand and fine content. The sand and fine content have a correlation coefficient of -0.6388 and 0.6285, respectively.

2) Using BFGs Quasi – Newton (BFG) Algorithm Based Neural Network Model

The artificial neural networks have been developed to predict the PI of soil using BFGs Quasi-Newton algorithm. The performance of BFG algorithm-based models is given in Table 13.

TABLE 13. PERFORMANCE OF BFG ALGORITHM-BASED ANN MODELS FOR PLASTICITY INDEX

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 116	1/5	0.0935	0.9701	0.0187	0.0892	0.9650	0.0201	4.9753	0.7455	3.8509
Model 117	1/10	0.0909	0.9734	0.1052	0.1199	0.9363	0.1119	5.2781	0.7248	4.2919
Model 118	1/15	0.0903	0.9739	0.3404	0.1085	0.9501	0.3699	4.0540	0.8136	3.6020
Model 119	2/5	0.0779	0.9765	0.0169	0.1049	0.9658	0.0240	5.2405	0.7193	4.2056
Model 120	2/10	0.2148	0.8252	0.8001	0.1829	0.8590	0.7908	4.7546	0.5132	3.3324
Model 121	2/15	0.1035	0.9609	0.0942	0.1256	0.9448	0.0931	5.5184	0.4683	3.9483
Model 122	3/5	0.0878	0.9713	0.0704	0.0698	0.9840	0.0696	5.1475	0.7375	4.2221
Model 123	3/10	0.1035	0.9591	0.1689	0.0907	0.9743	0.1703	4.0392	0.7668	3.3132
Model 124	3/15	0.0713	0.9817	0.0402	0.0934	0.9675	0.0476	5.5487	0.6159	4.2370
Model 125	4/5	0.0952	0.9641	0.0357	0.0976	0.9729	0.0495	4.8545	0.7606	3.9656
Model 126	4/10	0.0825	0.9733	0.0905	0.1079	0.9664	0.1012	4.4803	0.7581	3.8422
Model 127	4/15	0.0787	0.9796	0.1087	0.0907	0.9582	0.1086	5.4533	0.5946	4.0945
Model 128	5/5	0.0943	0.9671	0.0638	0.1213	0.9469	0.0677	5.0909	0.7280	4.3143
Model 129	5/10	0.0641	0.9856	0.0236	0.1226	0.9398	0.0408	5.3113	0.6075	4.0433
Model 130	5/15	0.0970	0.9650	0.2262	0.1104	0.9571	0.2225	5.1203	0.6536	4.2295

From Table 13, it has been observed that the BFG algorithm-based ANN model predicted the plasticity index of soil with a performance of 0.8136. Therefore, it may be stated that the BFG algorithm-based ANN model (1/15) predicts the plasticity index of soil better than the LM algorithm-based ANN model (2/15).

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3) Using Scaled Conjugate Gradient (SCG) Algorithm Based Neural Network Models

Artificial neural networks have been developed to predict the PI of soil using the SCG algorithm. The performance of SCG algorithm-based models is given in Table 14.

TABLE 14. PERFORMANCE OF SCG ALGORITHM-BASED ANN MODELS FOR PLASTICITY INDEX

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 131	1/5	0.1134	0.9530	0.0401	0.1116	0.9543	0.0376	5.3133	0.7383	4.1421
Model 132	1/10	0.0996	0.9632	0.0745	0.1122	0.9586	0.0740	5.2070	0.7598	4.2620
Model 133	1/15	0.1527	0.9153	0.0734	0.1631	0.9160	0.0667	4.4898	0.7870	3.6426
Model 134	2/5	0.1042	0.9594	0.0377	0.0889	0.9741	0.0395	6.1795	0.6507	5.0980
Model 135	2/10	0.0963	0.9648	0.0303	0.0893	0.9739	0.0299	5.4668	0.6314	4.2369
Model 136	2/15	0.1088	0.9550	0.1768	0.1287	0.9445	0.1912	6.3156	0.5099	4.6700
Model 137	3/5	0.1177	0.9518	0.0435	0.0954	0.9627	0.0433	4.3151	0.7152	3.4263
Model 138	3/10	0.1349	0.9304	0.1242	0.1601	0.9034	0.1175	5.0833	0.6563	4.0188
Model 139	3/15	0.0966	0.9667	0.0575	0.1151	0.9487	0.0615	5.2317	0.5974	4.3147
Model 140	4/5	0.1052	0.9586	0.0477	0.1124	0.9574	0.0523	4.9502	0.6578	3.7365
Model 141	4/10	0.1108	0.9546	0.0776	0.1378	0.9305	0.0730	4.4070	0.5932	3.0585
Model 142	4/15	0.1199	0.9432	0.2529	0.1401	0.9379	0.2662	4.3419	0.7153	3.4916
Model 143	5/5	0.1234	0.9436	0.0522	0.1188	0.9514	0.0526	6.1962	0.5843	4.9523
Model 144	5/10	0.0888	0.9735	0.0409	0.0606	0.9836	0.0384	5.2205	0.6406	4.3422
Model 145	5/15	0.0830	0.9756	0.0334	0.1017	0.9604	0.0377	4.7150	0.7059	3.7745

From Table 13, it has been observed that the SCG algorithm-based ANN model predicted the plasticity index of soil with a performance of 0.7870. It has also been observed that SCG algorithm-based ANN models require strongly correlated sand and fine content with PI.

4) Using Gradient Descent with Momentum (GDM) Algorithm Based Neural Network Models

Artificial neural networks have been developed to predict the PI of soil using the GDM algorithm. The performance of GDM algorithm-based models is given in Table 15.

TABLE 15. PERFORMANCE OF GDM ALGORITHM-BASED ANN MODELS FOR PLASTICITY INDEX

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 146	1/5	0.1275	0.9341	0.0315	0.1597	0.9210	0.0410	5.8063	0.5329	4.3796
Model 147	1/10	0.2056	0.8588	0.1252	0.1745	0.8292	0.0922	5.5386	0.4632	4.0688
Model 148	1/15	0.1609	0.9108	0.0493	0.1841	0.8824	0.0579	6.2310	0.7868	4.9162
Model 149	2/5	0.1792	0.8735	0.0528	0.2163	0.8207	0.0748	5.5847	0.4952	3.9170
Model 150	2/10	0.4208	0.6620	0.8106	0.4382	0.5575	0.8466	6.4502	0.3498	5.7947
Model 151	2/15	0.4506	0.6964	1.0730	0.3700	0.7432	1.0210	7.4952	0.6257	6.2392
Model 152	3/5	0.1965	0.8559	0.0636	0.1962	0.8335	0.0639	3.2702	0.8634	2.8181
Model 153	3/10	0.1490	0.9122	0.0389	0.1624	0.9082	0.0367	4.0890	0.7743	3.2545
Model 154	3/15	0.4209	0.6295	0.6229	0.3634	0.6984	0.5678	5.9679	0.6241	4.7362
Model 155	4/5	0.2241	0.7920	0.0769	0.2295	0.8039	0.0971	4.3599	0.4138	3.1822
Model 156	4/10	0.1617	0.8922	0.0424	0.1898	0.8911	0.0484	3.7304	0.7417	2.8517
Model 157	4/15	0.1852	0.8700	0.0487	0.1640	0.8941	0.0432	4.4936	0.6526	3.2588
Model 158	5/5	0.2124	0.8351	0.0547	0.2174	0.7880	0.0559	3.8733	0.7155	2.9629
Model 159	5/10	0.1314	0.9381	0.0230	0.1403	0.9156	0.0285	5.9709	0.5926	4.7706
Model 160	5/15	0.3055	0.7717	0.1800	0.2556	0.8153	0.2205	6.9119	0.5209	6.0766

From Table 15, it has been observed that the GDM algorithm-based ANN model predicted the plasticity index of soil with a performance of 0.8634. Therefore, it can be stated that the GDM algorithm-based ANN model (3/5) predicts the plasticity index of soil better than the LM, BFG, and SCG algorithm-based ANN model.

5) Using Gradient Descent (GD) Algorithm Based Neural Network Models

Artificial neural networks have been developed to predict the PI of soil using the GD algorithm. The performance of GD algorithm-based models is given in Table 16.

TABLE 16. PERFORMANCE OF GD ALGORITHM-BASED ANN MODELS FOR PLASTICITY INDEX

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 161	1/5	0.1685	0.8932	0.0491	0.1963	0.8474	0.0615	3.5745	0.7395	2.7924
Model 162	1/10	0.2333	0.7942	0.1062	0.2269	0.7747	0.1036	4.5789	0.6249	3.5532
Model 163	1/15	0.1426	0.9262	0.0391	0.1605	0.9173	0.0504	6.3462	0.5045	4.9682
Model 164	2/5	0.2320	0.7730	0.0954	0.2225	0.8363	0.1084	3.9751	0.7387	2.9780
Model 165	2/10	0.1529	0.9077	0.0474	0.1591	0.9146	0.0545	4.7277	0.6081	3.2716
Model 166	2/15	0.1882	0.8487	0.0741	0.1867	0.8967	0.0702	4.0714	0.6305	3.2137
Model 167	3/5	0.1632	0.8955	0.0622	0.1665	0.9034	0.0700	2.8608	0.8266	2.1785
Model 168	3/10	0.1772	0.8690	0.0635	0.2010	0.8762	0.0722	4.8797	0.4923	3.6017
Model 169	3/15	0.1559	0.9066	0.0594	0.1827	0.8737	0.0911	6.4048	0.3190	4.4622
Model 170	4/5	0.1675	0.8930	0.0666	0.1434	0.9241	0.0619	5.3178	0.5393	4.3517
Model 171	4/10	0.2106	0.8217	0.0626	0.2136	0.8223	0.0628	4.7407	0.6330	3.6126
Model 172	4/15	0.1516	0.9126	0.0377	0.2133	0.8217	0.0662	3.6665	0.6589	2.2443
Model 173	5/5	0.1977	0.8387	0.0708	0.2096	0.8487	0.0775	5.6564	0.4076	3.8573
Model 174	5/10	0.1786	0.8695	0.0644	0.2069	0.8474	0.0830	4.1612	0.5799	3.1377
Model 175	5/15	0.1607	0.9078	0.0500	0.1554	0.8942	0.0457	4.3096	0.6299	2.9803

From Table 16, it has been observed that the GD algorithm-based ANN model has predicted the plasticity index of soil with the performance of 0.8266. Therefore, it can be stated that the GD algorithm-based ANN model (3/5) predicts the plasticity index of soil better than the LM, BFG, and SCG algorithm-based ANN model.

6) Using Gradient Descent Algorithm with Adaptive Learning (GDA) Based Neural Network Model

Artificial neural networks have been developed to predict the PI of soil using the GDA algorithm. The performance of GDA algorithm-based models is given in Table 17.

TABLE 17. PERFORMANCE OF GDA ALGORITHM-BASED ANN MODELS FOR PLASTICITY INDEX

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 176	1/5	0.2440	0.7465	0.1692	0.2618	0.7436	0.1945	5.2705	0.4981	3.7032
Model 177	1/10	0.1551	0.9139	0.3170	0.1644	0.8905	0.2432	5.2917	0.6726	4.4011
Model 178	1/15	0.2018	0.8768	0.2652	0.1827	0.8731	0.2668	5.1596	0.5690	4.0081
Model 179	2/5	0.1436	0.9250	0.1544	0.1390	0.9275	0.1423	4.1891	0.6730	3.3252
Model 180	2/10	0.1677	0.9034	0.1316	0.1418	0.9297	0.1126	3.2423	0.7988	2.4588
Model 181	2/15	0.1424	0.9287	0.1842	0.1386	0.9138	0.1584	3.7145	0.7413	2.9625
Model 182	3/5	0.1583	0.9108	0.0454	0.1350	0.9213	0.0370	3.3477	0.7436	2.5612
Model 183	3/10	0.1744	0.8935	0.0768	0.1975	0.8265	0.0849	4.1701	0.7038	3.1721
Model 184	3/15	0.1276	0.9424	0.1979	0.1336	0.9307	0.1958	3.9659	0.8136	3.3663
Model 185	4/5	0.2025	0.8492	0.1367	0.1734	0.8717	0.1174	5.7265	0.3395	4.2076
Model 186	4/10	0.1334	0.9331	0.0631	0.1648	0.9027	0.0729	3.5543	0.7998	2.9269
Model 187	4/15	0.1688	0.9002	0.0790	0.1402	0.9137	0.0671	5.0080	0.6400	4.2041
Model 188	5/5	0.1438	0.9269	0.1962	0.1335	0.9238	0.1725	3.9148	0.7363	3.3099
Model 189	5/10	0.2122	0.8335	0.2008	0.2096	0.7989	0.1711	5.6389	0.3715	3.8897
Model 190	5/15	0.1519	0.9128	0.0545	0.1604	0.9174	0.0668	5.8969	0.3584	4.2640

From Table 17, it has been observed that the GDA algorithm-based ANN model has predicted the plasticity index of soil with a performance of 0.8136. Therefore, it can be stated that the GD algorithm-based ANN model (3/15) predicts the plasticity index of soil better than the LM and SCG algorithm-based ANN models.

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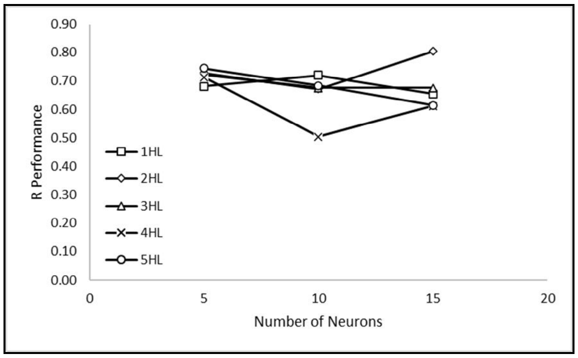
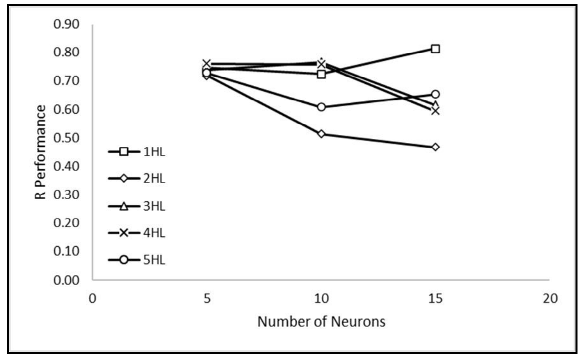
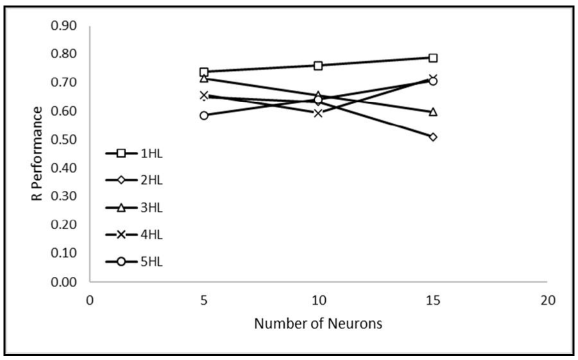
The performance variation of ANN models configured with different backpropagation algorithms for predicting soil plasticity index has been mapped, as shown in Fig. 4.



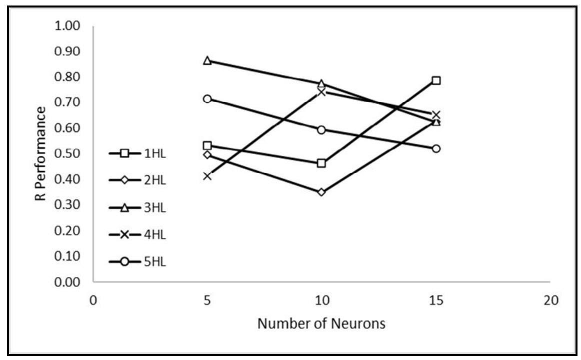
(a) Performance variation of ANN models configured with LM



(b) Performance variation of ANN models configured with BFG

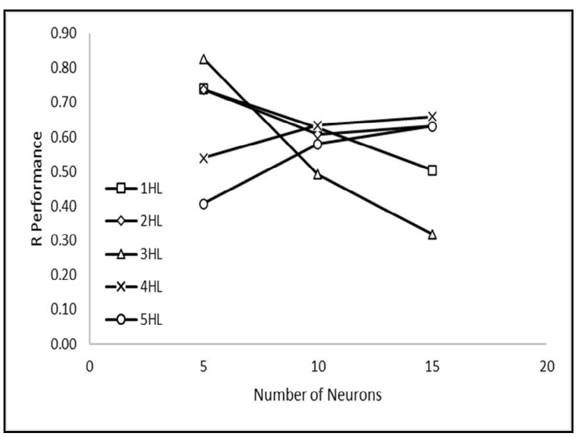


(c) Performance variation of ANN models configured with SCG

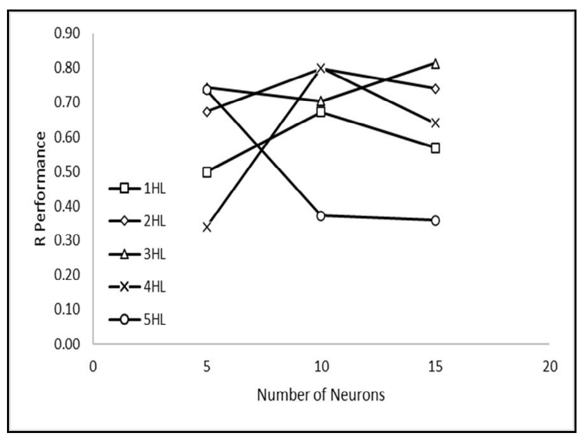


(d) Performance variation of ANN models configured with GDM

Fig. 4. Performance variation of ANN models in predicting plasticity index of soil (Conti…)



(e) Performance variation of ANN models configured with GD



(f) Performance variation of ANN models configured with GDA

Fig. 4. Performance variation of ANN models in predicting plasticity index of soil

Fig. 4 depicts the performance variation of ANN models configured with different backpropagation algorithms in predicting the plasticity index of soil. The same pattern is mapped in the performance variation of ANN models in predicting soil plasticity index. In a few cases, the performance of ANN models has continuously decreased in predicting the plasticity index. On the other hand, the maximum performance has been achieved by GDM algorithm-based ANN models in predicting the plasticity index of soil. Therefore, it may be stated that the GDM achieves better performance with a strongly correlated pair of datasets.

C. Prediction of Optimum Moisture Content

The LM, BFG, SCG, GDA, GD, and GDM algorithm-based artificial neural network models have evolved with many hidden layers and neurons to predict optimum moisture content. The performance of the proposed models has been discussed below.

1) Using Levenberg – Marquardt (LM) Algorithm Based Neural Network Models

The artificial neural networks have been developed to predict the OMC of soil using the LM algorithm. The performance of LM algorithm-based models is given in Table 18.

TABLE 18. PERFORMANCE OF LM ALGORITHM-BASED ANN MODELS FOR OPTIMUM MOISTURE CONTENT

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 201	1/5	0.0605	0.9706	0.0230	0.0610	0.9623	0.0263	1.5358	0.9822	1.1660
Model 202	1/10	0.0669	0.9722	0.0642	0.0736	0.9624	0.0903	2.4959	0.9721	1.7462
Model 203	1/15	0.0562	0.9731	0.0131	0.0642	0.9666	0.0158	1.9915	0.9629	1.3352
Model 204	2/5	0.0558	0.9746	0.0066	0.0604	0.9662	0.0064	2.2406	0.9531	1.3220
Model 205	2/10	0.0464	0.9823	0.0186	0.0860	0.9515	0.0228	2.3150	0.9656	1.3379
Model 206	2/15	0.0456	0.9824	0.0124	0.0724	0.9601	0.0186	2.2340	0.9401	1.5465
Model 207	3/5	0.0619	0.9695	0.0154	0.0666	0.9602	0.0171	2.4152	0.9527	1.6730
Model 208	3/10	0.0713	0.9623	0.0125	0.0660	0.9662	0.0127	2.3889	0.9552	2.0151
Model 209	3/15	0.0523	0.9775	0.0256	0.0867	0.9345	0.0272	1.6212	0.9553	1.4029
Model 210	4/5	0.0722	0.9531	0.0665	0.0784	0.9559	0.0744	1.6893	0.9509	1.2188
Model 211	4/10	0.0468	0.9790	0.0692	0.0812	0.9560	0.0718	1.8736	0.9632	1.3584
Model 212	4/15	0.0394	0.9869	0.0401	0.0655	0.9635	0.0542	2.5502	0.8963	1.8446
Model 213	5/5	0.0529	0.9772	0.0112	0.0763	0.9561	0.0155	2.7043	0.9745	1.5588
Model 214	5/10	0.0373	0.9889	0.0574	0.0820	0.9408	0.0600	1.8102	0.9715	1.4766
Model 215	5/15	0.0458	0.9841	0.4867	0.0780	0.9453	0.4955	1.8096	0.9387	1.2529

From Table 18, it has been observed that the performance of LM algorithm-based ANN models has been increased with the increasing number of hidden layers and neurons. The performance of two hidden layers-based models has been increased for two hidden layers interconnected with ten neurons, i.e., 0.9656. Similarly, the performance of the three hidden layers-based models has been increased for three hidden layers interconnected with 15 neurons, i.e., 0.9553. All LM algorithm-based ANN models predicted optimum moisture content with a performance of greater than 0.95 because of the correlation coefficient between input parameters (S, FC, & PL strongly correlated, and LL & PI very strongly correlated) and optimum moisture content.

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2) Using BFGs Quasi – Newton (BFG) Algorithm Based Neural Network Models

Artificial neural networks have been developed to predict the OMC of soil using the BFG algorithm. The performance of BFG algorithm-based models is given in Table 19.

TABLE 19. PERFORMANCE OF BFG ALGORITHM-BASED ANN MODELS FOR OPTIMUM MOISTURE CONTENT

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 216	1/5	0.0715	0.9536	0.0410	0.0726	0.9612	0.0410	2.9144	0.8917	2.1400
Model 217	1/10	0.0668	0.9611	0.0170	0.0752	0.9567	0.0179	1.7998	0.9545	1.4806
Model 218	1/15	0.0708	0.9550	0.0221	0.0823	0.9508	0.0222	2.1371	0.9071	1.6924
Model 219	2/5	0.0738	0.9508	0.0238	0.0727	0.9585	0.0261	1.7524	0.9351	1.4130
Model 220	2/10	0.0568	0.9740	0.0097	0.0652	0.9574	0.0098	1.4624	0.9786	1.0831
Model 221	2/15	0.0529	0.9787	0.0625	0.0910	0.9025	0.0675	2.2724	0.9172	1.8292
Model 222	3/5	0.0678	0.9617	0.0268	0.0689	0.9580	0.0258	1.4354	0.9580	1.2417
Model 223	3/10	0.0867	0.9389	0.1075	0.0838	0.9420	0.1082	2.0696	0.9201	1.6577
Model 224	3/15	0.0792	0.9527	0.0855	0.0823	0.9177	0.0813	2.8382	0.8921	2.1297
Model 225	4/5	0.0734	0.9547	0.0165	0.0757	0.9498	0.0167	1.4980	0.9621	1.2470
Model 226	4/10	0.0622	0.9665	0.0191	0.0671	0.9651	0.0209	1.4774	0.9646	1.1394
Model 227	4/15	0.0647	0.9648	0.0339	0.0748	0.9529	0.0417	1.5236	0.9647	1.2510
Model 228	5/5	0.0735	0.9574	0.1000	0.0785	0.9365	0.0955	1.8488	0.9317	1.5298
Model 229	5/10	0.0877	0.9381	0.1304	0.1044	0.8863	0.1319	2.3121	0.8919	1.6981
Model 230	5/15	0.0729	0.9511	0.0741	0.0788	0.9547	0.0720	2.1630	0.8979	1.6666

Table 19 shows that the BFG algorithm-based ANN models predict the optimum moisture content with a performance of more than 0.85. It has also been observed that the BFG algorithm-based ANN models require two or four hidden layers with ten neurons to achieve a performance of more than 0.96. Model 220 outperformed the other BFG algorithm-based ANN models in predicting optimum moisture content.

3) Using Scaled Conjugate Gradient (SCG) Algorithm Based Neural Network Models

The artificial neural networks have been developed to predict the OMC of soil using the SCG algorithm. The performance of SCG algorithm-based models is given in Table 20.

TABLE 20. PERFORMANCE OF SCG ALGORITHM-BASED ANN MODELS FOR OPTIMUM MOISTURE CONTENT

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 231	1/5	0.0678	0.9615	0.0485	0.0674	0.9584	0.0474	1.4750	0.9741	1.2795
Model 232	1/10	0.0678	0.9604	0.0201	0.0937	0.9269	0.0233	3.0644	0.9002	2.0679
Model 233	1/15	0.0662	0.9590	0.0483	0.0637	0.9720	0.0461	1.5230	0.9789	1.2279
Model 234	2/5	0.0674	0.9548	0.0220	0.0647	0.9726	0.0275	1.2389	0.9750	0.9399
Model 235	2/10	0.0597	0.9664	0.0241	0.0712	0.9642	0.0322	2.1166	0.9561	1.5072
Model 236	2/15	0.0617	0.9695	0.0344	0.0755	0.9446	0.0336	2.2469	0.9172	1.6116
Model 237	3/5	0.0593	0.9714	0.0153	0.0626	0.9630	0.0157	1.3359	0.9693	1.1181
Model 238	3/10	0.0546	0.9714	0.0183	0.0755	0.9668	0.0237	3.1326	0.8816	1.5863
Model 239	3/15	0.0875	0.9358	0.2965	0.1079	0.8932	0.3150	2.4866	0.8813	1.9214
Model 240	4/5	0.0862	0.9384	0.0259	0.0721	0.9530	0.0243	1.8769	0.9250	1.4832
Model 241	4/10	0.0749	0.9523	0.0155	0.0955	0.9310	0.0257	2.0971	0.9782	1.7799
Model 242	4/15	0.0628	0.9654	0.0212	0.0715	0.9590	0.0232	1.9577	0.9284	1.5763
Model 243	5/5	0.0779	0.9506	0.0617	0.0775	0.9402	0.0661	3.5013	0.8829	2.3629
Model 244	5/10	0.0679	0.9586	0.0289	0.0785	0.9532	0.0344	1.7440	0.9598	1.5105
Model 245	5/15	0.0686	0.9584	0.0710	0.0842	0.9447	0.0740	1.4522	0.9557	1.0662

Table 20 shows that Model 233 outperformed the other SCG algorithm-based ANN models in predicting the OMC of soil. However, table 20 also indicates that the performance of the SCG algorithm-based ANN model has been decreased with increasing the number of hidden layers.

4) Using Gradient Descent with Momentum (GDM) Algorithm Based Neural Network Models

Artificial neural networks have been developed to predict the OMC of soil using the GDM algorithm. The performance of GDM algorithm-based models is given in Table 21.

TABLE 21. PERFORMANCE OF GDM ALGORITHM-BASED ANN MODELS FOR OPTIMUM MOISTURE CONTENT

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 246	1/5	0.1284	0.9370	0.0229	0.1379	0.9702	0.0274	2.5919	0.8718	1.8263
Model 247	1/10	0.1075	0.8982	0.0234	0.1178	0.8935	0.0236	3.9374	0.7318	3.2326
Model 248	1/15	0.1378	0.8213	0.0530	0.1846	0.7386	0.0664	3.9058	0.6097	3.2454
Model 249	2/5	0.0958	0.9241	.0.2264	0.0765	0.9489	0.0165	2.1606	0.9010	1.7428
Model 250	2/10	0.1163	0.8839	0.0399	0.1780	0.7857	0.0600	3.3881	0.7874	2.4571
Model 251	2/15	0.0986	0.9163	0.0235	0.1017	0.9046	0.0235	2.0266	0.9284	1.6979
Model 252	3/5	0.1202	0.8660	0.0239	0.1136	0.8966	0.0223	2.1769	0.9416	1.7989
Model 253	3/10	0.0965	0.9107	0.0226	0.1085	0.9170	0.0323	2.3178	0.8995	1.9568
Model 254	3/15	0.2845	0.8126	0.3002	0.2883	0.8191	0.2870	3.7777	0.7643	2.5276
Model 255	4/5	0.1293	0.8465	0.0238	0.1463	0.8069	0.0274	2.3765	0.9150	1.9466
Model 256	4/10	0.0872	0.9353	0.0152	0.0930	0.9225	0.0150	2.5965	0.8977	1.9193
Model 257	4/15	0.2345	0.8597	0.2320	0.2467	0.7845	0.2468	3.2685	0.8848	2.5851
Model 258	5/5	0.1515	0.7726	0.0404	0.1533	0.8334	0.0448	3.7520	0.8194	3.3550
Model 259	5/10	0.0928	0.9212	0.0151	0.1199	0.8959	0.0230	2.5180	0.8914	2.1143
Model 260	5/15	0.1604	0.7499	0.3260	0.1525	0.7977	0.3020	2.9102	0.8415	2.4376

From Table 21, it has been observed that the performance of the GDM algorithm-based ANN model has been increased up to three hidden layers. On the other hand, the performance of GDM models has been decreasing with increasing the number of hidden layers in the prediction of OMC.

5) Using Gradient Descent (GD) Algorithm Based Neural Network Models

The artificial neural networks have been developed to predict the OMC of soil using the GD algorithm. The performance of GD algorithm-based models is given in Table 22.

TABLE 22. PERFORMANCE OF GD ALGORITHM-BASED ANN MODELS FOR OPTIMUM MOISTURE CONTENT

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 261	1/5	0.1087	0.8969	0.0318	0.1415	0.8219	0.0417	3.0967	0.8560	2.5154
Model 262	1/10	0.1234	0.8701	0.0273	0.1241	0.8705	0.0223	3.3938	0.8091	2.4948
Model 263	1/15	0.1279	0.8785	0.0630	0.1274	0.8921	0.0725	3.6624	0.8819	2.7955
Model 264	2/5	0.0999	0.9078	0.0381	0.1199	0.8850	0.0406	3.4192	0.8731	2.4869
Model 265	2/10	0.1365	0.8394	0.0328	0.1299	0.8244	0.0287	2.2094	0.9353	1.7116
Model 266	2/15	0.1088	0.9051	0.0491	0.1030	0.9049	0.0365	3.2638	0.7712	2.3701
Model 267	3/5	0.1250	0.8614	0.0318	0.1321	0.7945	0.0288	2.8298	0.8505	2.2730
Model 268	3/10	0.0896	0.9345	0.0164	0.1235	0.8697	0.0232	2.7791	0.8942	1.6670
Model 269	3/15	0.0876	0.9402	0.0157	0.0956	0.8952	0.0198	2.0383	0.9345	1.5937
Model 270	4/5	0.1792	0.6910	0.0684	0.1633	0.7299	0.0633	3.5938	0.7817	3.1359
Model 271	4/10	0.0913	0.9259	0.0214	0.0907	0.9324	0.0213	3.3093	0.8569	2.8472
Model 272	4/15	0.0874	0.9339	0.0133	0.0968	0.9229	0.0157	1.8525	0.9316	1.4624
Model 273	5/5	0.1201	0.8708	0.0458	0.1412	0.8239	0.0534	2.0147	0.9300	1.6181
Model 274	5/10	0.1235	0.8681	0.0294	0.1417	0.7971	0.0300	3.0886	0.8084	2.6045
Model 275	5/15	0.0779	0.9467	0.0114	0.0890	0.9365	0.0140	2.6987	0.9137	2.0070

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From Table 22, it has been observed that the performance of GD algorithm-based ANN models has been started increasing up to two hidden layers. Therefore, the ANN model of two hidden layers interconnected with ten neurons has been identified as a better performance model. However, from Table 22, it has also been observed that the performance of GD ANN models decreased with hidden layers after two layers in predicting the OMC of soil.

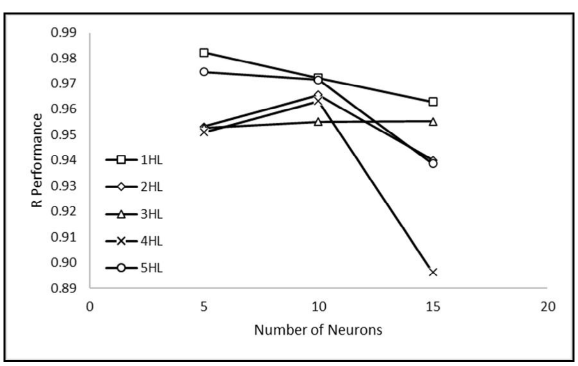
6) Using Gradient Descent Algorithm with Adaptive Learning (GDA) Based Neural Network Models

The artificial neural networks have been developed to predict the OMC of soil using the GDA algorithm. The performance of GDA algorithm-based models is given in Table 23.

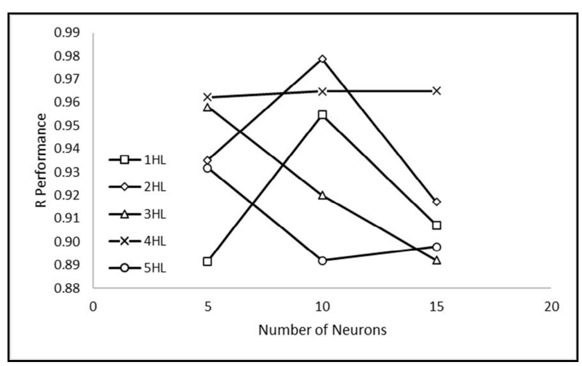
TABLE 23. PERFORMANCE OF GDA ALGORITHM-BASED ANN MODELS FOR OPTIMUM MOISTURE CONTENT

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 276	1/5	0.0801	0.9477	0.0582	0.0951	0.9336	0.0760	1.7522	0.9437	1.3095
Model 277	1/10	0.0884	0.9361	0.0689	0.0864	0.9250	0.0727	3.8420	0.8210	3.1291
Model 278	1/15	0.0943	0.9235	0.0472	0.1352	0.8492	0.0442	2.8842	0.8203	2.1718
Model 279	2/5	0.1035	0.9122	0.0569	0.1037	0.8989	0.0651	3.1994	0.7596	2.5478
Model 280	2/10	0.0848	0.9339	0.0239	0.0896	0.9467	0.0317	1.5136	0.9515	1.1409
Model 281	2/15	0.1184	0.8983	0.0363	0.1111	0.8853	0.0363	5.2495	0.5519	3.5770
Model 282	3/5	0.0910	0.9299	0.0331	0.0975	0.9212	0.0351	2.2330	0.9249	1.8035
Model 283	3/10	0.0964	0.9293	0.1079	0.1015	0.9095	0.0798	2.2151	0.9021	1.7263
Model 284	3/15	0.0713	0.9580	0.0315	0.0951	0.9266	0.0364	2.9364	0.8708	2.1602
Model 285	4/5	0.0925	0.9324	0.0645	0.0907	0.9262	0.0766	2.1903	0.9075	1.7804
Model 286	4/10	0.0849	0.9398	0.0452	0.0868	0.9299	0.0411	2.7128	0.8504	2.1271
Model 287	4/15	0.1035	0.9168	0.1039	0.1015	0.8900	0.0890	1.6273	0.8952	1.1139
Model 288	5/5	0.1015	0.9134	0.2014	0.1077	0.9026	0.1889	2.8014	0.8308	2.2104
Model 289	5/10	0.1182	0.8799	0.0457	0.1138	0.8881	0.0481	2.9885	0.8236	2.4389
Model 290	5/15	0.0971	0.9342	0.0293	0.1109	0.8885	0.0375	2.3855	0.8779	1.8470

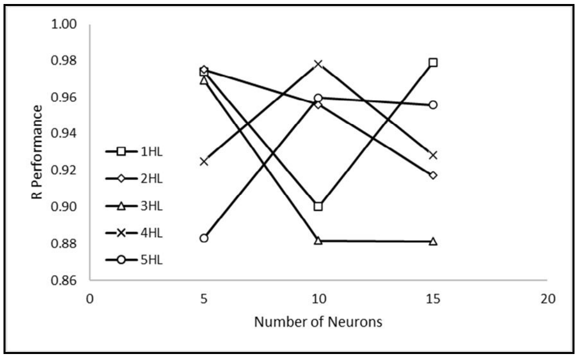
From Table 23, it has been observed that the performance of GDA algorithm-based ANN models has been started increasing up to two hidden layers. Therefore, the ANN model of two hidden layers interconnected with ten neurons has been identified as a better performance model. From Table 23, it has also been observed that the performance of GDA ANN models decreased with hidden layers after two layers in predicting the OMC of soil. The performance variation of ANN models configured with different backpropagation algorithms for predicting soil optimum moisture content has been mapped, as shown in Fig. 5.



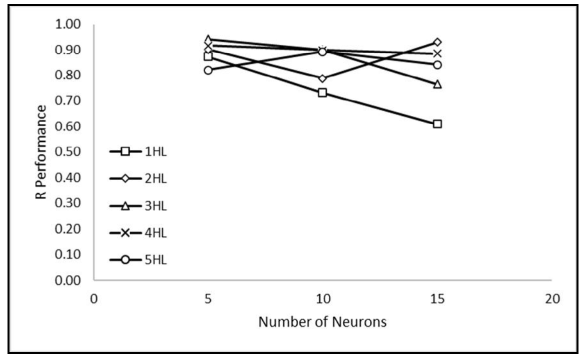
(a) Performance variation of ANN models configured with LM



(b) Performance variation of ANN models configured with BFG

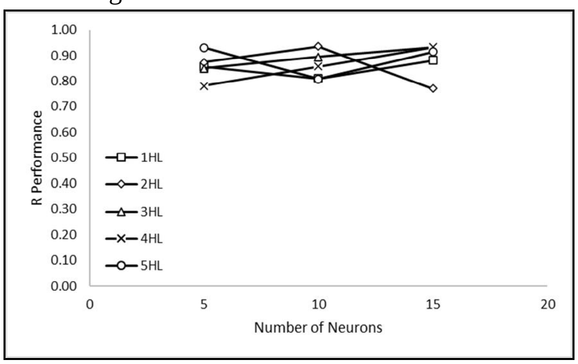


(c) Performance variation of ANN models configured with SCG

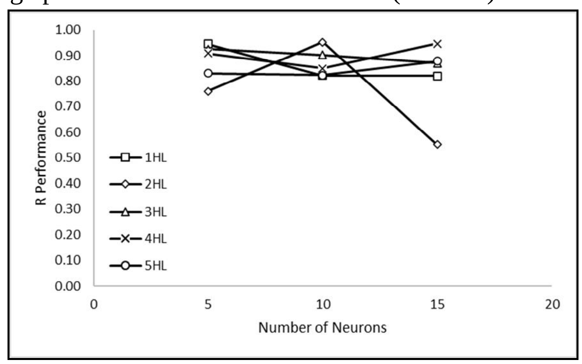


(d) Performance variation of ANN models configured with GDM

Fig. 5. Performance variation of ANN models in predicting optimum moisture content of soil (Conti…)



(e) Performance variation of ANN models configured with GD



(f) Performance variation of ANN models configured with GDA

Fig. 5. Performance variation of ANN models in predicting optimum moisture content of soil

Fig. 5 depicts the performance variation of ANN models configured with different backpropagation algorithms in predicting the OMC of soil. The same pattern is mapped in the performance variation of ANN models in predicting the OMC of soil. In a few cases, the performance of ANN models has continuously decreased in predicting OMC. On the other hand, the maximum performance has been achieved by LM algorithm-based ANN models in predicting the OMC of soil. Therefore, it may be stated that the LM achieves better performance due to the strongly correlated datasets.

D. Prediction of Maximum Dry Density

For the prediction of maximum dry density, the LM, BFG, SCG, GDA, GD, and GDM algorithm-based artificial neural network models have evolved with different hidden layers and neurons. The performance of the proposed models has been discussed below.

1) Using Levenberg – Marquardt (LM) Algorithm Based Neural Network Models

The artificial neural networks have been developed to predict the MDD of soil using the LM algorithm. The performance of LM algorithm-based models is given in Table 24.

TABLE 24. PERFORMANCE OF LM ALGORITHM-BASED ANN MODELS FOR MAXIMUM DRY DENSITY

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 301	1/5	0.0099	0.9760	0.0005	0.0111	0.9645	0.0004	0.1161	0.8754	0.0925
Model 302	1/10	0.0100	0.9762	0.0008	0.0108	0.9659	0.0006	0.1027	0.9474	0.0743
Model 303	1/15	0.0087	0.9795	0.0008	0.0112	0.9729	0.0010	0.1068	0.9609	0.0866
Model 304	2/5	0.0104	0.9747	0.0007	0.0097	0.9711	0.0007	0.0917	0.9318	0.0654
Model 305	2/10	0.0091	0.9809	0.0017	0.0126	0.9485	0.0017	0.0828	0.9474	0.0580
Model 306	2/15	0.0090	0.9834	0.0028	0.0112	0.9551	0.0030	0.0805	0.9627	0.0608
Model 307	3/5	0.0091	0.9814	0.0008	0.0108	0.9628	0.0008	0.0765	0.9606	0.0647

Model 308	3/10	0.0088	0.9813	0.0020	0.0113	0.9665	0.0020	0.0831	0.9166	0.0625
Model 309	3/15	0.0092	0.9792	0.0022	0.0113	0.9698	0.0019	0.0935	0.9618	0.0799
Model 310	4/5	0.0093	0.9801	0.0075	0.0112	0.9596	0.0075	0.0844	0.9470	0.0611
Model 311	4/10	0.0097	0.9793	0.0012	0.0107	0.9697	0.0012	0.0715	0.9503	0.0539
Model 312	4/15	0.0104	0.9741	0.0015	0.0133	0.9599	0.0016	0.0700	0.9784	0.0532
Model 313	5/5	0.0092	0.9786	0.0022	0.0114	0.9691	0.0024	0.0733	0.9230	0.0566
Model 314	5/10	0.0096	0.9774	0.0009	0.0130	0.9626	0.0012	0.0892	0.9487	0.0738
Model 315	5/15	0.0093	0.9787	0.0008	0.0105	0.9703	0.0008	0.0878	0.9588	0.0592

From Table 24, it has been observed that the performance of one, two, four, and five hidden layer-based ANN models have been increased with the number of neurons. But the performance of three hidden layer-based ANN models has decreased by providing ten neurons. Nevertheless, model 312 outperformed the other LM models in predicting the maximum dry density of soil with a performance of 0.9784.

2) Using BFGs Quasi – Newton (BFG) Algorithm Based Neural Network Models

Artificial neural networks have been developed to predict the MDD of soil using the BFG algorithm. The performance of BFG algorithm-based models is given in Table 25.

TABLE 25. PERFORMANCE OF BFG ALGORITHM-BASED ANN MODELS FOR MAXIMUM DRY DENSITY

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 316	1/5	0.0134	0.9500	0.0011	0.0165	0.9479	0.0013	0.0648	0.9145	0.0490
Model 317	1/10	0.0120	0.9658	0.0018	0.0123	0.9540	0.0018	0.0898	0.9494	0.0612
Model 318	1/15	0.0110	0.9696	0.0024	0.0110	0.9701	0.0022	0.0812	0.9654	0.0651
Model 319	2/5	0.0170	0.9116	0.0024	0.0180	0.9418	0.0028	0.0580	0.9556	0.0520
Model 320	2/10	0.0188	0.9195	0.0018	0.0174	0.8779	0.0017	0.0568	0.9252	0.0292
Model 321	2/15	0.0127	0.9589	0.0037	0.0115	0.9687	0.0037	0.0857	0.9597	0.0650
Model 322	3/5	0.0195	0.9066	0.0014	0.0164	0.9225	0.0012	0.0939	0.8981	0.0787
Model 323	3/10	0.0160	0.9318	0.0009	0.0128	0.9621	0.0010	0.0851	0.9042	0.0732
Model 324	3/15	0.0219	0.8694	0.0070	0.0257	0.8465	0.0070	0.1066	0.7436	0.0602
Model 325	4/5	0.0139	0.9480	0.0015	0.0147	0.9572	0.0016	0.0633	0.9506	0.0474
Model 326	4/10	0.0166	0.9287	0.0011	0.0153	0.9398	0.0011	0.0811	0.9349	0.0725
Model 327	4/15	0.0135	0.9474	0.0007	0.0213	0.9090	0.0011	0.0734	0.9540	0.0570
Model 328	5/5	0.0135	0.9535	0.0006	0.0144	0.9477	0.0007	0.0731	0.9006	0.0550
Model 329	5/10	0.0106	0.9711	0.0006	0.0133	0.9537	0.0006	0.0882	0.9378	0.0605
Model 330	5/15	0.0130	0.9565	0.0008	0.0112	0.9728	0.0008	0.0667	0.9030	0.0528

From Table 25, it has been observed that the performance of the single-hidden layers-based ANN model has increased with neurons. But it has also been observed that the performance of three and five hidden layers-based ANN models has been increased by providing ten neurons. Model 318 has been identified as a better performance model in predicting MDD of soil with a performance of 0.9654.

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3) Using Scaled Conjugate Gradient (SCG) Algorithm Based Neural Network Models

Artificial neural networks have been developed to predict the MDD of soil using the SCG algorithm. The performance of SCG algorithm-based models is given in Table 26.

TABLE 26. PERFORMANCE OF SCG ALGORITHM-BASED ANN MODELS FOR MAXIMUM DRY DENSITY

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 331	1/5	0.0131	0.9557	0.0003	0.0138	0.9520	0.0004	0.0705	0.9623	0.0597
Model 332	1/10	0.0107	0.9718	0.0004	0.0113	0.9645	0.0003	0.0904	0.9379	0.0643
Model 333	1/15	0.0177	0.9141	0.0022	0.0164	0.9405	0.0018	0.0903	0.9560	0.0832
Model 334	2/5	0.0117	0.9624	0.0003	0.0134	0.9603	0.0004	0.0891	0.9428	0.0592
Model 335	2/10	0.0096	0.9742	0.0011	0.0141	0.9578	0.0013	0.1153	0.9223	0.0929
Model 336	2/15	0.0107	0.9719	0.0006	0.0130	0.9543	0.0007	0.0665	0.9302	0.0511
Model 337	3/5	0.0137	0.9550	0.0004	0.0134	0.9455	0.0004	0.0731	0.8818	0.0592
Model 338	3/10	0.0121	0.9603	0.0005	0.0157	0.9434	0.0006	0.0854	0.8866	0.0515
Model 339	3/15	0.0156	0.9417	0.0033	0.0149	0.9385	0.0031	0.1143	0.8740	0.0872
Model 340	4/5	0.0123	0.9571	0.0007	0.0138	0.9612	0.0008	0.0747	0.9214	0.0471
Model 341	4/10	0.0142	0.9416	0.0013	0.0157	0.9485	0.0019	0.1045	0.8639	0.0695
Model 342	4/15	0.0109	0.9693	0.0013	0.0112	0.9693	0.0013	0.0854	0.9496	0.0569
Model 343	5/5	0.0126	0.9604	0.0009	0.0128	0.9543	0.0009	0.0759	0.9593	0.0635
Model 344	5/10	0.0106	0.9736	0.0020	0.0128	0.9518	0.0020	0.0771	0.9435	0.0532
Model 345	5/15	0.0122	0.9603	0.0008	0.0158	0.9498	0.0010	0.1095	0.9274	0.0839

From Table 26, it has been observed that the SCG algorithm-based ANN models have achieved maximum performance using one to five hidden layers interconnected with 5/15 neurons. Model 331 has outperformed the other SCG ANN models in predicting MDD of soil with a performance of 0.9623.

4) Using Gradient Descent with Momentum (GDM) Algorithm Based Neural Network Models

Artificial neural networks have been developed to predict the MDD of soil using the GDM algorithm. The performance of GDM algorithm-based models is given in Table 27.

TABLE 27. PERFORMANCE OF GDM ALGORITHM-BASED ANN MODELS FOR MAXIMUM DRY DENSITY

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 346	1/5	0.0318	0.7485	0.0012	0.0372	0.6603	0.0016	0.0839	0.8709	0.0611
Model 347	1/10	0.0392	0.7343	0.0051	0.0436	0.8088	0.0053	0.0736	0.8629	0.0556
Model 348	1/15	0.0493	0.5174	0.0049	0.0542	0.3973	0.0053	0.1661	0.5749	0.1430
Model 349	2/5	0.0586	0.7148	0.0105	0.0656	0.7697	0.0128	0.2382	0.5828	0.2145
Model 350	2/10	0.0399	0.7892	0.0022	0.0349	0.8114	0.0016	0.1378	0.5118	0.1142
Model 351	2/15	0.0673	0.4501	0.0091	0.0527	0.7228	0.0081	0.2582	0.6403	0.2322
Model 352	3/5	0.0295	0.8610	0.0013	0.0319	0.8419	0.0016	0.0975	0.8256	0.0829
Model 353	3/10	0.0384	0.6660	0.0045	0.0341	0.6778	0.0041	0.0875	0.7619	0.0679
Model 354	3/15	0.0399	0.6777	0.0059	0.0413	0.6427	0.0063	0.1277	0.3487	0.1060
Model 355	4/5	0.0346	0.6837	0.0016	0.0273	0.7019	0.0011	0.1361	0.6427	0.1187
Model 356	4/10	0.0324	0.7980	0.0019	0.0322	0.8077	0.0023	0.0806	0.8176	0.0542
Model 357	4/15	0.0334	0.7413	0.0025	0.0334	0.8268	0.0028	0.1980	0.7026	0.1505
Model 358	5/5	0.0555	0.5570	0.0126	0.0500	0.5499	0.0110	0.1343	0.5305	0.0886
Model 359	5/10	0.0358	0.6657	0.0069	0.0440	0.6018	0.0081	0.1652	0.4309	0.1288
Model 360	5/15	0.0352	0.6392	0.0042	0.0362	0.6139	0.0041	0.1734	0.3052	0.1076

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From Table 27, it has been observed that the performance of GDM algorithm-based ANN models has been decreased with the number of hidden layers. It has also been observed that the GDM ANN models have less capacity in predicting the MDD of soil. The training performance of developed models is less than 0.9. Therefore, the GDM ANN models have not achieved performance equal to or more than 0.9. Model 346 has been identified as a better performance model in predicting MDD of soil with a performance of 0.8709.

5) Using Gradient Descent (GD) Algorithm Based Neural Network Models

Artificial neural networks have been developed to predict the MDD of soil using the GD algorithm. The performance of GD algorithm-based models is given in Table 28.

TABLE 28. PERFORMANCE OF GD ALGORITHM-BASED ANN MODELS FOR MAXIMUM DRY DENSITY

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 361	1/5	0.0318	0.7484	0.0012	0.0372	0.6602	0.0016	0.0840	0.8708	0.0611
Model 362	1/10	0.0539	0.4981	0.0039	0.0488	0.4842	0.0032	0.2275	0.6592	0.1801
Model 363	1/15	0.0760	0.7989	0.0104	0.0852	0.7581	0.0128	0.2411	0.8963	0.1977
Model 364	2/5	0.0486	0.3981	0.0043	0.0489	0.6733	0.0050	0.1366	0.5304	0.1100
Model 365	2/10	0.0566	0.8936	0.0064	0.0671	0.9105	0.0089	0.1886	0.9117	0.1174
Model 366	2/15	0.0428	0.6924	0.0185	0.0574	0.6729	0.0176	0.3063	0.8548	0.2559
Model 367	3/5	0.0456	0.8158	0.0044	0.0433	0.8827	0.0035	0.1466	0.7977	0.0935
Model 368	3/10	0.0624	0.5455	0.0119	0.0720	0.6377	0.0146	0.2700	0.6445	0.2372
Model 369	3/15	0.0337	0.7264	0.0055	0.0257	0.8272	0.0046	0.0931	0.7454	0.0843
Model 370	4/5	0.0374	0.6219	0.0024	0.0363	0.7380	0.0024	0.0895	0.7544	0.0804
Model 371	4/10	0.0386	0.8349	0.0062	0.0452	0.8215	0.0066	0.1142	0.8327	0.0860
Model 372	4/15	0.0281	0.8093	0.0023	0.0248	0.8230	0.0019	0.1281	0.7927	0.0967
Model 373	5/5	0.0265	0.8615	0.0008	0.0253	0.8238	0.0008	0.1080	0.8586	0.0867
Model 374	5/10	0.0268	0.8118	0.0011	0.0355	0.7089	0.0018	0.0600	0.9462	0.0498
Model 375	5/15	0.0395	0.6910	0.0039	0.0337	0.6571	0.0030	0.1310	0.7885	0.1099

From Table 28, it has been observed that the GD algorithm-based ANN model has predicted MDD of soil with a performance of less than 0.8, which is less acceptable. Therefore, model 374 has been identified as a better performance model in predicting MDD of soil with a performance of 0.9462.

6) Using Gradient Descent Algorithm with Adaptive Learning (GDA) Based Neural Network Models

Artificial neural networks have been developed to predict the MDD of soil using the GDA algorithm. The performance of GDA algorithm-based models is given in Table 29.

TABLE 29. PERFORMANCE OF GDA ALGORITHM-BASED ANN MODELS FOR MAXIMUM DRY DENSITY

Model ID	HL/N	Training			Validation			Testing		
		RMSE	R	MAE	RMSE	R	MAE	RMSE	R	MAE
Model 376	1/5	0.0138	0.9540	0.0025	0.0125	0.9553	0.0022	0.1172	0.9186	0.0938
Model 377	1/10	0.0140	0.9502	0.0081	0.0155	0.9451	0.0097	0.1438	0.8354	0.1014
Model 378	1/15	0.0154	0.9437	0.0018	0.0143	0.9368	0.0016	0.1161	0.9642	0.0952
Model 379	2/5	0.0203	0.8985	0.0014	0.0193	0.8968	0.0021	0.0945	0.7407	0.0574
Model 380	2/10	0.0134	0.9545	0.0280	0.0141	0.9579	0.0266	0.0661	0.9598	0.0537
Model 381	2/15	0.0143	0.9524	0.0027	0.0178	0.9102	0.0028	0.0656	0.9490	0.0543
Model 382	3/5	0.0158	0.9362	0.0029	0.0152	0.9466	0.0030	0.1103	0.8490	0.0857
Model 383	3/10	0.0173	0.9198	0.0126	0.0172	0.9415	0.0133	0.0997	0.8452	0.0776
Model 384	3/15	0.0171	0.9351	0.0110	0.0175	0.8902	0.0117	0.1399	0.7945	0.0998
Model 385	4/5	0.0137	0.9485	0.0005	0.0131	0.9669	0.0006	0.0881	0.9428	0.0745
Model 386	4/10	0.0156	0.9387	0.0061	0.0287	0.7949	0.0077	0.0839	0.7981	0.0568
Model 387	4/15	0.0179	0.9196	0.0074	0.0191	0.8982	0.0068	0.1095	0.8881	0.0896
Model 388	5/5	0.0153	0.9390	0.0042	0.0185	0.9193	0.0045	0.0783	0.9501	0.0705
Model 389	5/10	0.0221	0.8763	0.0032	0.0225	0.8692	0.0033	0.1065	0.8193	0.0953
Model 390	5/15	0.0175	0.9169	0.0035	0.0230	0.9018	0.0048	0.0801	0.8948	0.0685

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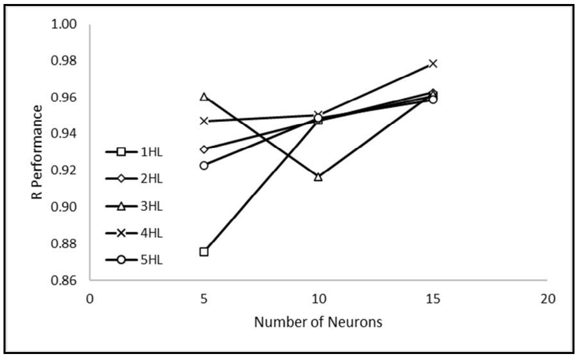
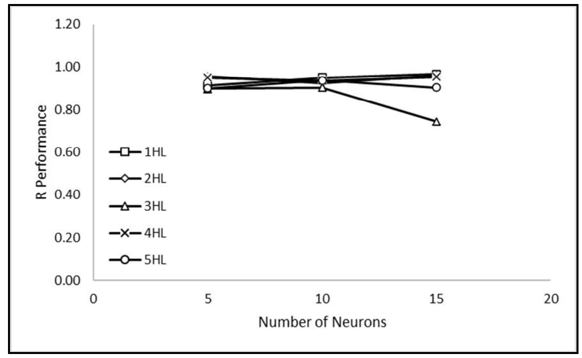
From Table 29, it has been observed that the GDA algorithm-based ANN models employed with 5/15 neurons have predicted MDD of soil with a performance of more than 0.85. Thus, Model 378 has been identified as a better performance model with a performance of 0.9642.

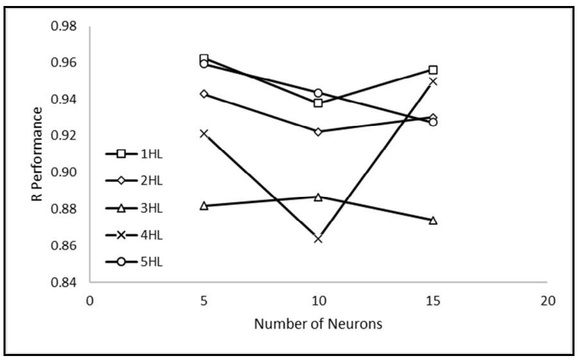
The performance variation of ANN models configured with different backpropagation algorithms for predicting soil optimum moisture content has been mapped, as shown in Fig. 6.



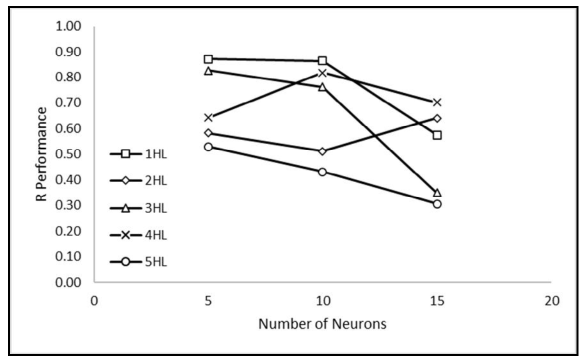
(a) Performance variation of ANN models configured with LM



(b) Performance variation of ANN models configured with BFG

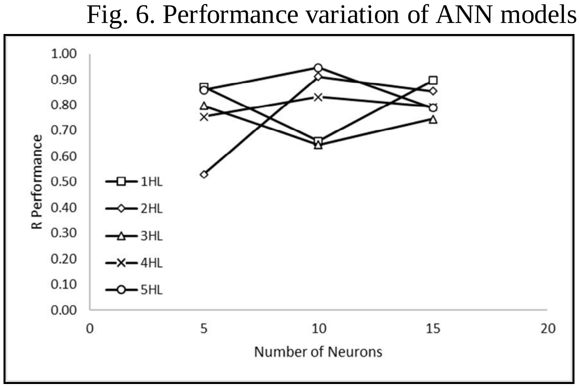


(c) Performance variation of ANN models configured with SCG

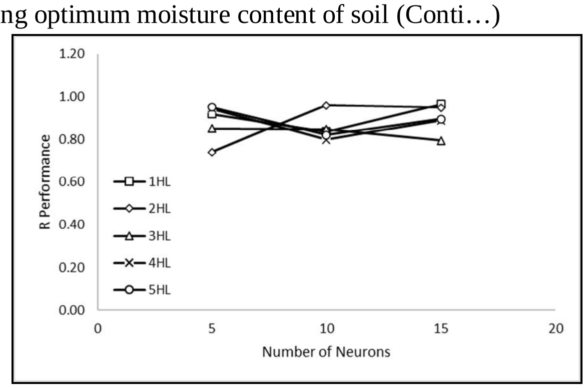


(d) Performance variation of ANN models configured with GDM

Fig. 6. Performance variation of ANN models in predicting optimum moisture content of soil (Conti…)



(e) Performance variation of ANN models configured with GD



(f) Performance variation of ANN models configured with GDA

Fig. 6. Performance variation of ANN models in predicting optimum moisture content of soil

Fig. 6 depicts the performance variation of ANN models configured with different backpropagation algorithms in predicting the MDD of soil. The same pattern is mapped in the performance variation of ANN models in predicting MDD of soil. In a few cases, the performance of ANN models has continuously decreased with neurons. The maximum performance has been achieved by LM algorithm-based ANN models in predicting the MDD of soil. Therefore, it may be stated that the LM achieves better performance due to the strongly correlated datasets.

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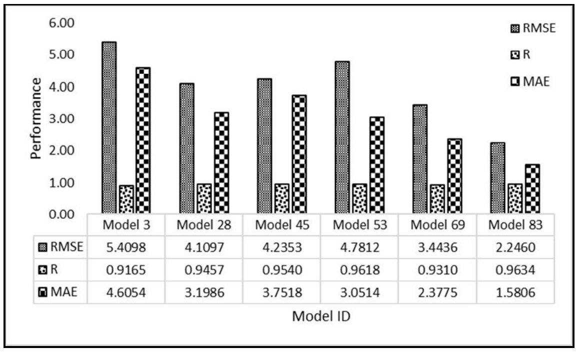
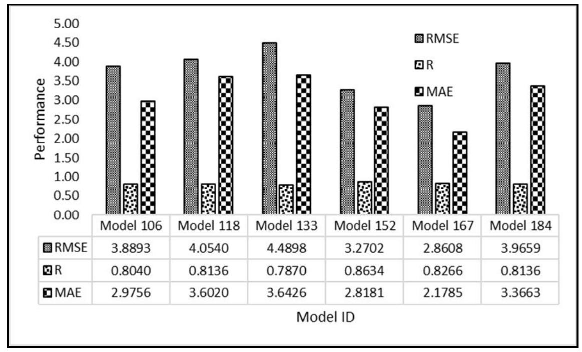
V. THE BEST ARCHITECTURE MODELS

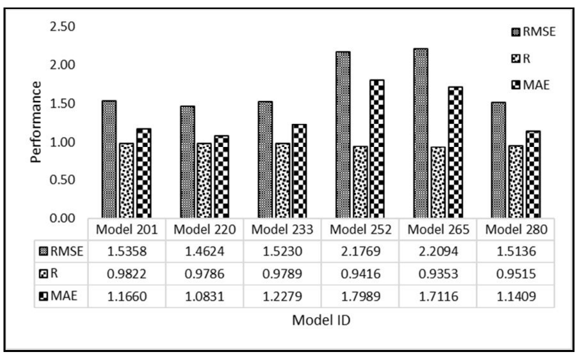
The present research work has been carried out to predict the liquid limit, plasticity index, optimum moisture content, and maximum dry density. A total of 390 ANN models have been developed in the present work to identify the best architectural ANN models for predicting the geotechnical properties of soil. Models 3, 28, 45, 53, 69, and 83 have been identified as better performance models in predicting the liquid limit of soil. Similarly, Models 106, 118, 133, 152, 167, and 184 have been identified as better performance models in predicting soil plasticity index. The compaction parameters, namely maximum dry density and optimum moisture content, have also been predicted using artificial neural networks. Models 201, 220, 233, 252, 265, and 280 have been identified as better performance models in predicting the OMC of soil. Similarly, Models 312, 318, 331, 346, 374, and 378 have been identified as the better performance models in predicting MDD of soil. Finally, the best architectural ANN models have been identified by comparing the performance of better performance models, as shown in Fig. 7.



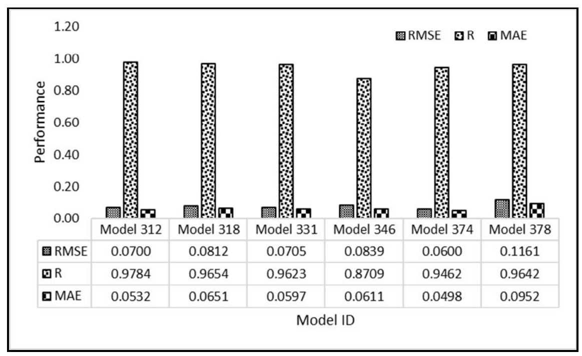
(a) Performance comparison of better performance models of LL



(b) Performance comparison of better performance models of PI



(c) Performance comparison of better performance models of OMC



(d) Performance comparison of better performance models of MDD

Fig. 7. Performance comparison of better performance models

Fig. 7 depicts the performance comparison of the better performance models to identify the best architectural ANN Models for predicting LL, PI, OMC, and MDD of soil. Figure 7(a) shows that Model 83 has outperformed Models 3, 28, 45, 53, and 69 in predicting the liquid limit of soil with the performance of 0.9634. Figure 7(b) shows that Model 152 has outperformed Models 106, 118, 133, 167, and 184 in predicting the plasticity index of soil with a performance of 0.8634. Figure 7(c) shows that Model 201 has outperformed Models 220, 233, 252, 265, and 280 in predicting the OMC of soil. Figure 7 (d) shows that Model 312 has outperformed Models 318, 331, 346, 374, and 378 in predicting the MDD of soil. Models 83, 152, 201, and 312 have been configured with 3HL/10N, 3HL/5N, 1HL/5N, and 4HL/15N. Similarly, it has also been observed that the GDA algorithm-based ANN model has predicted LL with optimum performance of 0.9634, having strongly correlated datasets. But in the case of PI, the GDM algorithm-based ANN model has achieved a performance of 0.8634, having strongly correlated datasets. The LM, BFG, and SCG algorithm-based ANN models did not perform well. Therefore, models 201 and 312 of OMC and MDD have been identified as the best architectural ANN models. Models 201 and 312 have been configured with the LM backpropagation algorithm. The input (S, FC, LL, PI) and output (OMC, MDD) compaction parameters are strongly to very strongly correlated. Therefore, it may be stated that the LM backpropagation algorithm-based ANN model requires strongly to very strongly correlated datasets to achieve higher performance and prediction accuracy. The artificial neural network models have been classified based on their performance, as shown in Fig. 8.

	LM	BFG	SCG	GDM	GD	GDA
1HL	15N	10N	15N	10N	10N	5N
	0.9165	0.9357	0.9139	0.9122	0.9094	0.9223
2HL	5N	15N	15N	5N	10N	15N
	0.8918	0.8855	0.9081	0.8867	0.8721	0.9330
3HL	10N	5N	10N	10N	15N	10N
	0.8847	0.9308	0.9289	0.9618	0.9310	0.9634
4HL	5N	5N	5N	15N	5N	5N
	0.8921	0.9193	0.9274	0.9325	0.8178	0.8651
5HL	15N	5N	15N	15N	15N	5N
	0.9017	0.9457	0.9540	0.9513	0.8797	0.8997

(a) Performance of ANN models in predicting LL

	LM	BFG	SCG	GDM	GD	GDA
1HL	10N	15N	15N	15N	5N	10N
	0.7205	0.8136	0.7870	0.7868	0.7395	0.6726
2HL	15N	5N	5N	15N	5N	10N
	0.8040	0.7193	0.6507	0.6257	0.7387	0.7988
3HL	5N	10N	5N	5N	5N	15N
	0.7235	0.7668	0.7152	0.8634	0.8266	0.8136
4HL	5N	5N	15N	10N	15N	10N
	0.7141	0.7606	0.7153	0.7417	0.6589	0.7998
5HL	5N	5N	15N	5N	15N	5N
	0.7452	0.7280	0.7059	0.7155	0.6299	0.7363

(b) Performance of ANN models in predicting PI

	LM	BFG	SCG	GDM	GD	GDA
1HL	5N	10N	15N	5N	15N	5N
	0.9822	0.9545	0.9741	0.8718	0.8819	0.9437
2HL	10N	10N	5N	15N	10N	10N
	0.9656	0.9786	0.9750	0.9284	0.9353	0.9515
3HL	15N	5N	5N	5N	15N	5N
	0.9553	0.9580	0.9693	0.9416	0.9305	0.9249
4HL	10N	15N	10N	5N	15N	15N
	0.9632	0.9647	0.9782	0.9150	0.9316	0.9452
5HL	5N	5N	10N	10N	5N	10N
	0.9745	0.9317	0.9598	0.8914	0.9316	0.8779

(c) Performance of ANN models in predicting OMC

	LM	BFG	SCG	GDM	GD	GDA
1HL	5N	15N	5N	5N	15N	15N
	0.9609	0.9654	0.9623	0.8709	0.8963	0.9642
2HL	15N	15N	5N	15N	10N	10N
	0.9627	0.9597	0.9428	0.6403	0.9117	0.9598
3HL	15N	10N	10N	5N	5N	5N
	0.9618	0.9042	0.8866	0.8256	0.7977	0.8490
4HL	15N	15N	15N	10N	10N	5N
	0.9784	0.9540	0.9496	0.8176	0.8327	0.9428
5HL	15N	10N	5N	5N	10N	5N
	0.9588	0.9378	0.9593	0.5305	0.9462	0.9501

(d) Performance of ANN models in predicting MDD

Fig. 8. Classification of ANN models based on performance

Fig. 8 depicts the classification of ANN models based on test performance. The artificial neural network model is classified as a robust, high, moderate, and good performance model if the model has a performance of more than 0.95, between 0.9-0.95, between 0.8-0.9, and less than 0.8, respectively. The following formulas have also been suggested for the required number of hidden layers and neurons to achieve robust or high-performance during prediction by ANN models. The suggested equations are applicable only for datasets with a correlation coefficient of more than 0.85.

For LM, BFG, and SCG algorithms

$$N' = 5 + \sqrt{I + O} \tag{12}$$

$$HL = \frac{\sqrt[8]{I - N' + 1}}{4} \tag{13}$$

For GDM, GD, and GDA algorithms

$$N' = \sqrt{I + O} - 5 \tag{14}$$

$$HL = \frac{\sqrt[8]{I - N' + 1}}{2} \tag{15}$$

Where N' is the number of neurons, HL is hidden layers, I is the number of input dataset (s), O is the output(s)

VI. CONCLUSIONS

The present research work was carried out to determine the best architecture models to predict soil's consistency limits and compaction parameters. On the other hand, hidden layers, neurons, and backpropagation algorithms were studied while predicting consistency limits and compaction parameters. The artificial neural network models were developed using the different number of hidden layers (one to five), neurons (5, 10 & 15), and backpropagation algorithms (LM, BFG, SCG, GDM, GD & GDA). The present study maps the following conclusions.

1) In the prediction of liquid limit, it was observed that the performance of the LM algorithm-based ANN model was decreased with increasing the number of hidden layers and neurons. On the other hand, the performance of BFG and SCG algorithm-based ANN models was increased by increasing the hidden layers and neurons. The performance of the GDA, GD and GDM algorithm-based ANN model was increased up to 3 hidden layers interconnecting with 10/15 neurons. Therefore, it may be stated that the LM requires the least hidden layers and neurons for achieving a performance of more than 0.9. Thus, Models 3 (LM), 28 (BFG), 45 (SCG), 53 (GDM), 69 (GD), and 83 (GDA) were identified as better performance models in predicting the liquid limit of soil. Models 3, 28, 45, 53, 69, and 83 showed that Model 83 outperformed other better performance liquid limit models with a performance of 0.9634.
2) In the prediction of plasticity index, it was observed that the performance of LM algorithm-based ANN models was increased up to two hidden layers interconnected with 15 neurons (Model 106). Further, the performance of the LM algorithm-based ANN model was started decreasing. The performance of the BFG and SCG algorithm-based ANN model decreased with an increasing number of hidden layers and neurons. On the other hand, the performance of the GDA, GD, and GDM algorithm-based ANN model was increased up to 3 hidden layers interconnected with 5/15 neurons. Therefore, it may be stated that the BFG and SCG algorithm-based ANN model requires the least hidden layer and neurons for achieving a performance of more than 0.75. Thus, Models 106, 118, 133, 152, 167, and 184 were identified as better performance models in predicting the plasticity index of soil. Models 106, 118, 133, 152, 167, and 184 showed that Model 152 outperformed other better performance plasticity index models with a performance of 0.8634.
3) In the prediction of optimum moisture content, it was observed that the performance of LM algorithm-based ANN models was decreased with the number of hidden layers and neurons (Models 201 to 215). The SCG algorithm-based ANN model 233 achieved a performance of 0.9789. Model 233 was configured with one hidden layer interconnected with 15 neurons. Similarly, the BFG algorithm-based ANN model 220 achieved a performance of 0.9786, which was close to the performance of Model 233. Model 220 was configured with two hidden layers interconnected with ten neurons. Furthermore, it was stated that the SCG algorithm-based ANN model 233 requires less hidden layers and neurons. The GDM, GD, and GDA algorithm-based ANN models achieved performance of 0.9416 (3 HL, 5N), 0.9353 (2HL, 10N), and 0.9515 (2HL, 10N), respectively. Thus, Models 201, 220, 233, 252, 265, and 280 were identified as better performance models in predicting the OMC of soil. Models 201, 220, 233, 252, 265, and 280 showed that Model 201 outperformed other better performance optimum moisture content models with a performance of 0.9822.
4) In the prediction of maximum dry density, it was observed that the performance of LM algorithm-based ANN models was increased with a number of hidden layers and neurons (Models 301 to 315). Model 312 predicted MDD of soil with a performance of 0.9784. The BFG and GDA algorithm-based ANN models predicted MDD of soil with a performance of 0.9654 and 0.9642, respectively. Therefore, it may be stated that the BFG and GDA algorithm achieves approximate equal performance if the model is configured with one hidden layer interconnected with 15 neurons. On the other hand, GDM and SCG algorithm-based ANN model's performance decreased with the increasing number of hidden layers and neurons. The GD algorithm-based ANN model achieved a performance of 0.9462 configured with five hidden layers interconnected with ten neurons. Thus, Models 312, 318, 331, 346, 374, and 378 were identified as the better performance model. The performance comparison showed that Model 312 outperformed the other ANN models in predicting the MDD of soil.

The above statements show that the performance of artificial neural networks is affected by the number of hidden layers, neurons, and backpropagation algorithms. Finally, it may be concluded that the consistency limits of soil may be predicted with high accuracy using LM (1HL, 15N), BFG (5HL, 5N), SCG (5HL, 15N), GDM (3HL, 10N), GD (3HL, 15N) and GDA (3HL, 10N) algorithms for ANN models. Similarly, the compaction parameters of soil may be predicted with high accuracy using LM (1HL, 5N), BFG (2HL, 10N), SCG (1HL, 15N), GDM (3HL, 5N), GD (2HL, 10N), and GDA (2HL, 10N) algorithms for ANN models. The strength parameters are affected by the size of the particle and consistency limits. Therefore, the proposed ANN models of compaction parameters can be used to predict the UCS, C, and phi parameters of soil.

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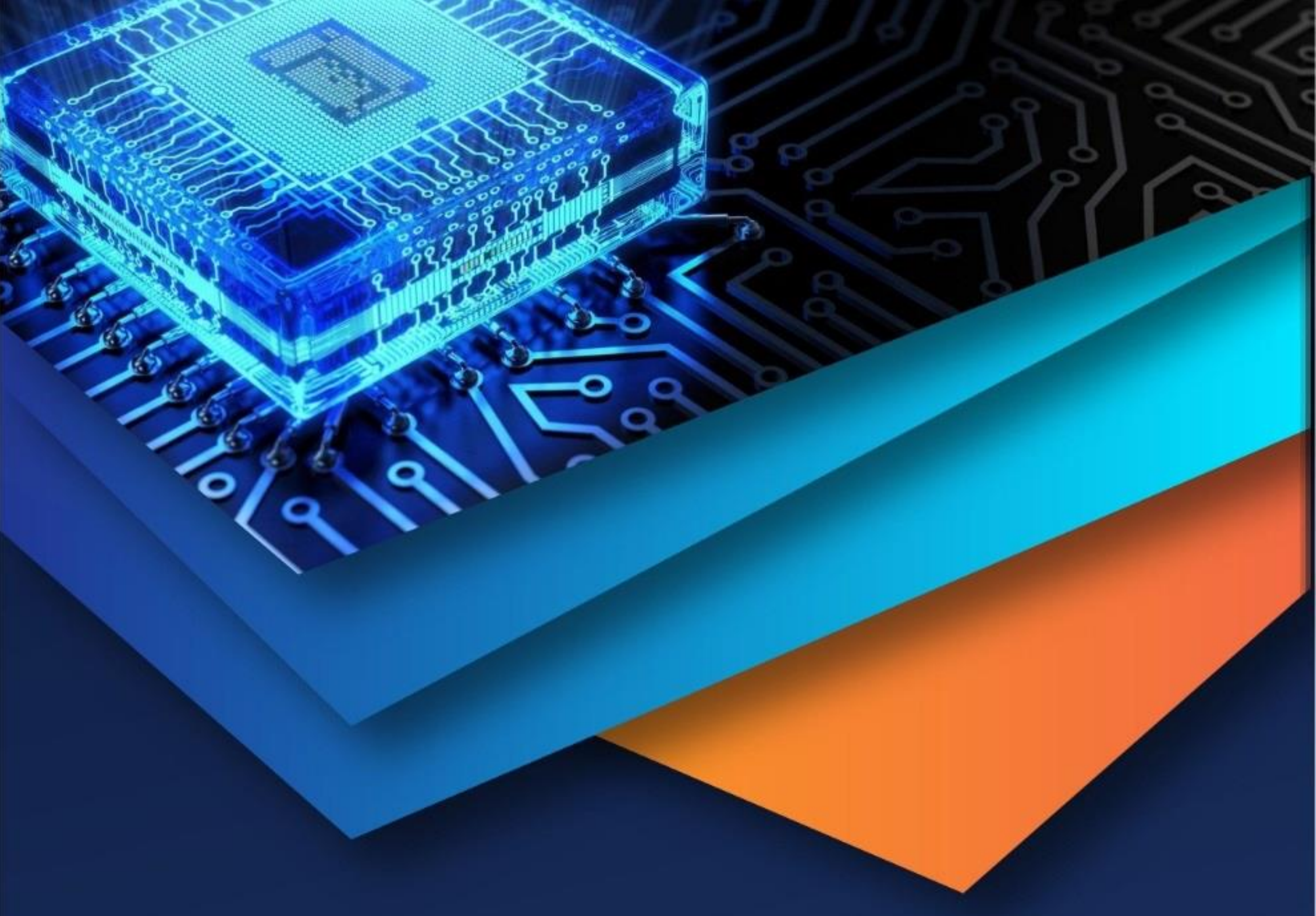

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