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Predicting the strength of a plastic waste reinforced clay-sand soil mixture using BPNN approach

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ABSTRACT

The study aimed to improve soil engineering properties by incorporating waste plastic bottle strips into the soil to enhance its strength. Plastic sheets of varying sizes an percentage were used, and a Back Propagation Neural Network (BPNN) was employed to predict unconfined compressive force. The model accuracy was confirmed by calculating mean absolute errors (MAE) of 0.00336, 0.0491, 0.0344, and 0.0461, indicating its reliability.

Keywords: *Back Propagation Neural Network, Waste Plastic Reinforcement, Unconfined Compression Tests.*

1. Introduction

In recent years, the volume of research and development in the field of Artificial Neural Networks (ANNs) has surged, garnering increasing attention for their ability to tackle a wide range of complex real-world problems compared to traditional methods [1].

Many applications of ANN models have been applied in the field of civil engineering due to their ability and immense flexibility in determining the complex relationships between input and output variables, which leads to extremely accurate predictions [2]. The back-propagation neural network (BPN) has been demonstrated to be a robust and effective prediction model, provided there is an adequate amount of training data [3].

In traditional soil improvement methods, laboratory testing through experimental trial and error is often used, but it can be difficult and time-consuming. However, some researchers in geotechnical engineering have started using AI techniques to analyze the optimal amounts of additives for soil improvement. One example of AI application in civil engineering is in geotechnical engineering, where the engineering properties of soil and rock vary widely and uncertainties arise due to the complex and imprecise physical processes involved in their formation [4].

Binh et al. [5] developed an Artificial Neural Network (ANN) model to predict the Soil Coefficient of Consolidation. They trained the model using a dataset of 188 test results and evaluated two ANN structures for accuracy. The results (RMSE = 0.0614, MAE = 0.0415, and R^2 = 0.99727) indicated that the ANN is a strong predictive model compared to the majority of the test data.

Van Quan Tran developed a back-propagation neural network (BPNN) model to predict the compressive strength of stabilized dredged sediments. The model underwent training on 70% of the dataset and was tested using the remaining 30%. The model's accuracy was confirmed by the mean absolute error (MAE) and root mean square error (RMSE) indicators, with MAE values of 3.9001 and 8.6535 for training and testing, and RMSE values of 9.1948 and 10.3390 for training and testing, respectively [6].

Galal H. Senussi successfully applied the Back Propagation Artificial Neural Network (BPNN) method to forecast the CO_2 corrosion penetration rate (CPR) of the Al-Sarir-Tobruk pipeline, which is utilized for crude oil transportation. Senussi devised a robust BPN model for predicting the CPR. The implemented simulation showcased the BPNN's ability to adjust the weight coefficients, even with a limited set of examples, to generate precise outputs based on the provided inputs. This was confirmed by a mean absolute error (MAE) of only 0.00457 mm/y, demonstrating the dependability and high effectiveness of the model [7].

2. Methodology

A methodology utilizing Artificial Neural Networks (ANN) has been employed to examine the increase in the ultimate shear strength of a soil mixture comprising 60% sand and 40% kaolin. This investigation involves the incorporation of waste plastic bottle strips at different percentages (WP%) through a series of unconfined compression tests [8].

Backpropagation is widely recognized as one of the most popular methods for training Artificial Neural Networks (ANN) due to its ability to effectively learn patterns and utilize a feedback technique to adjust its weights [9]. This method is designed to minimize the mean square error (MSE) between the actual values and the predicted values of the output from the training set using an iterative gradient descent algorithm [3].

In Figure 1, the process of creating the Back Propagation Neural Network (BPNN) model for the percentage increment in unconfined compressive strength (%qu) with different addition ratios of waste plastic strips (WP%) is illustrated [8]. The normalized data was input into the neural network after building the model. A training set, consisting of 70% of the data, was created, while the remaining 30% was used as a testing set for the final phase. After obtaining the results, the outputs are compared with the targeted values. If the output meets the criteria, the program concludes; otherwise, the model is adjusted.

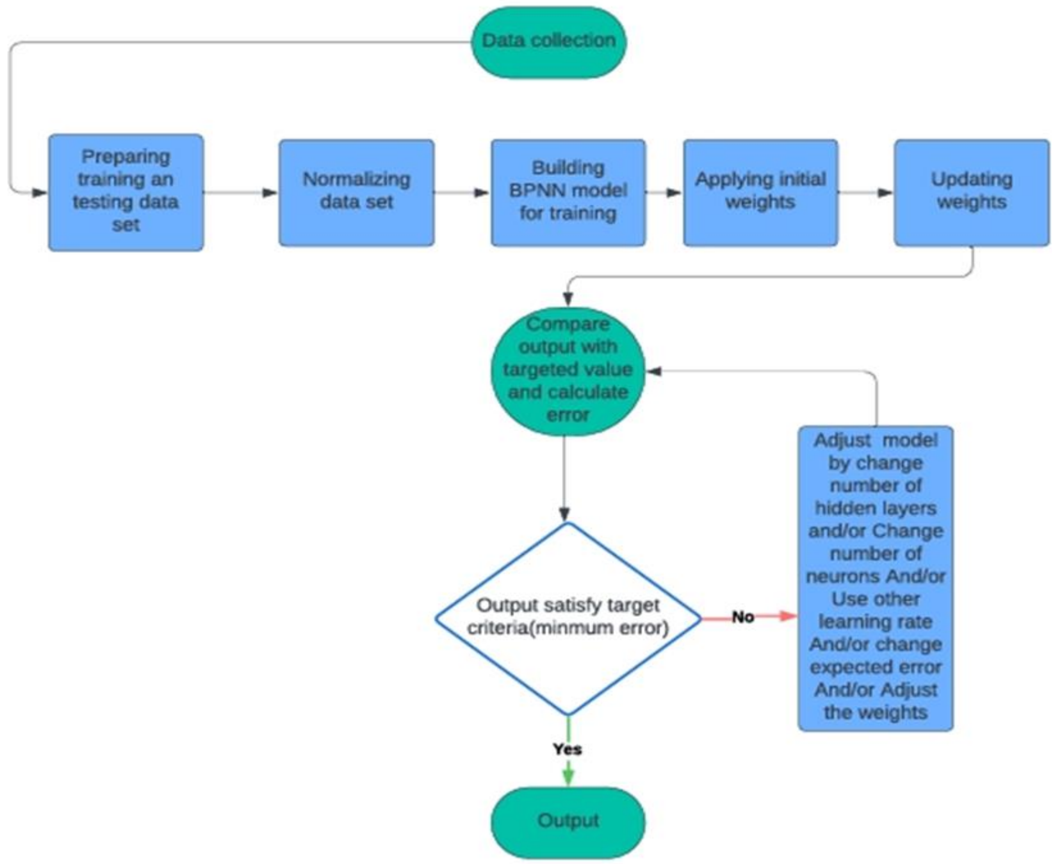

Figure1: Flow chart of developing BPNN model of percent increment in unconfined compressive strength for different addition ratios of plain plastic strips.

3. Experimental method analysis and results

The use of waste plastic bottle strips as a reinforcing material in soil is becoming more common to improve soil engineering properties. This study involved conducting a series of unconfined compression tests on clayey sand soil, both with and without the addition of plastic bottle strips, to examine how the inclusion of these plastic strips affects the soil's shear strength [8].

Unconfined compression test's main parameters with their respective ranges presented in Table1.

Table1 .parameters and corresponding ranges

Parameters	Notation	Unit	Range	
			Lower value	Upper value
Width	W	mm	1	3
Length	L	mm	5	15
Weight plastic	WP	%	0.25	1

The study utilizes the artificial neural back propagation network (BPNN) approach to develop a mathematical model for investigating the impact of incorporating waste plastic bottle strips on the unconfined pressure resistance of soil.

The essential steps in constructing an artificial neural network (ANN) model involve preparing and modeling the data, training and evaluating the neural network, and analyzing the outcomes to choose the optimal model. Here are additional details on the steps involved in building artificial neural networks (ANNs).

Table 2 shows experimental data on plastic strip addition ratio and dimensions (length and width) as input variables, along with unconfined compressive force, percentage increase in unconfined compressive force, axial strain ratio, and lateral strain ratio as outputs.

Table2. Real Values

Input data			Output data			
WP % (X1)	Width mm (X2)	Length Mm (X3)	qu kN/m2 (y1)	Axial Strain%(y2)	% qu Increment (y3)	Lateral Strain % (y4)
0.25	1	5	81.6	3.25	30.21	1.67
0.25	2	5	71.03	2.5	13.34	1.27
0.25	3	5	68.94	2.25	10	1.14
0.25	1	10	97.87	3.5	56.17	1.8
0.25	2	10	84.99	3.25	35.62	1.67
0.25	3	10	82.87	3	32.23	1.53
0.25	1	15	118.68	4.5	89.37	2.33
0.25	2	15	99.07	3.75	58.08	1.93
0.25	3	15	97.69	3.25	55.88	1.67
0.5	1	5	87.3	3.75	39.3	1.93
0.5	2	5	74.32	3	18.59	1.53
0.5	3	5	73.63	2.75	17.49	1.4
0.5	1	10	107.37	4.25	71.33	2.19
0.5	2	10	84.99	3.25	35.62	1.67
0.5	3	10	84.56	3	34.93	1.53
0.5	1	15	125.85	4.75	100.81	2.46
0.5	2	15	106.68	4.25	70.22	2.19
0.5	3	15	102.85	4	64.11	2.06
0.75	1	5	96.24	3.75	53.57	1.93
0.75	2	5	78.09	3.25	24.61	1.67
0.75	3	5	76.6	3	22.23	1.53
0.75	1	10	131.28	5.25	109.48	2.73
0.75	2	10	95.99	4	53.17	2.06
0.75	3	10	93.49	3.75	49.18	1.93
0.75	1	15	169.19	6	169.97	3.14
0.75	2	15	119.73	4.75	91.05	2.46
0.75	3	15	107.77	4.5	71.96	2.33
1	1	5	104.09	4.75	66.09	2.46
1	2	5	98.73	4	57.54	1.8
1	3	5	79.06	3.75	26.15	1.93
1	1	10	140.39	5.5	124	2.87
1	2	10	99.84	4.25	59.31	2.19
1	3	10	95.99	4	53.17	2.06
1	1	15	176.1	6.25	181	3.28
1	2	15	122.45	4.75	95.39	2.46
1	3	15	111.86	4.5	78.489	2.33

Table3. Normalizing Values

Input data			Output data			
x1	x2	x3	y1	y2	y3	y4
0	1	6.333333	0.118141	0.25	0.118187	0.247664
0	2.333333	6.333333	0.019504	0.0625	0.019532	0.060748
0	3.666667	6.333333	0	0	0	0
0	1	13	0.26997	0.3125	0.27	0.308411
0	2.333333	13	0.149776	0.25	0.149825	0.247664
0	3.666667	13	0.129993	0.1875	0.13	0.182243
0	1	19.66667	0.464166	0.5625	0.464152	0.556075
0	2.333333	19.66667	0.281168	0.375	0.28117	0.369159
0	3.666667	19.66667	0.26829	0.25	0.268304	0.247664
0.333333	1	6.333333	0.171333	0.375	0.171345	0.369159
0.333333	2.333333	6.333333	0.050205	0.1875	0.050234	0.182243
0.333333	3.666667	6.333333	0.043766	0.125	0.043801	0.121495
0.333333	1	13	0.358623	0.5	0.358655	0.490654
0.333333	2.333333	13	0.149776	0.25	0.149825	0.247664
0.333333	3.666667	13	0.145763	0.1875	0.145789	0.182243
0.333333	1	19.66667	0.531075	0.625	0.531053	0.616822
0.333333	2.333333	19.66667	0.352184	0.5	0.352164	0.490654
0.333333	3.666667	19.66667	0.316443	0.4375	0.316433	0.429907
0.666667	1	6.333333	0.254759	0.375	0.254795	0.369159
0.666667	2.333333	6.333333	0.085386	0.25	0.085439	0.247664
0.666667	3.666667	6.333333	0.071482	0.1875	0.07152	0.182243
0.666667	1	13	0.581747	0.75	0.581754	0.742991
0.666667	2.333333	13	0.252426	0.4375	0.252456	0.429907
0.666667	3.666667	13	0.229097	0.375	0.229123	0.369159
0.666667	1	19.66667	0.935517	0.9375	0.935497	0.934579
0.666667	2.333333	19.66667	0.473964	0.625	0.473977	0.616822
0.666667	3.666667	19.66667	0.362355	0.5625	0.362339	0.556075
1	1	6.333333	0.328014	0.625	0.328012	0.616822
1	2.333333	6.333333	0.277996	0.4375	0.278012	0.308411
1	3.666667	6.333333	0.094438	0.375	0.094444	0.369159
1	1	13	0.66676	0.8125	0.666667	0.808411
1	2.333333	13	0.288354	0.5	0.288363	0.490654
1	3.666667	13	0.252426	0.4375	0.252456	0.429907
1	1	19.66667	1	1	1	1
1	2.333333	19.66667	0.499347	0.625	0.499357	0.616822
1	3.666667	19.66667	0.400523	0.5625	0.40052	0.556075

The neural network architecture (3-3-4-5-6-4) produced satisfactory results. The network has an input layer with three neurons, followed by layers with three, four, five, and six neurons, and a final output layer with four neurons, as shown in Figure 2.

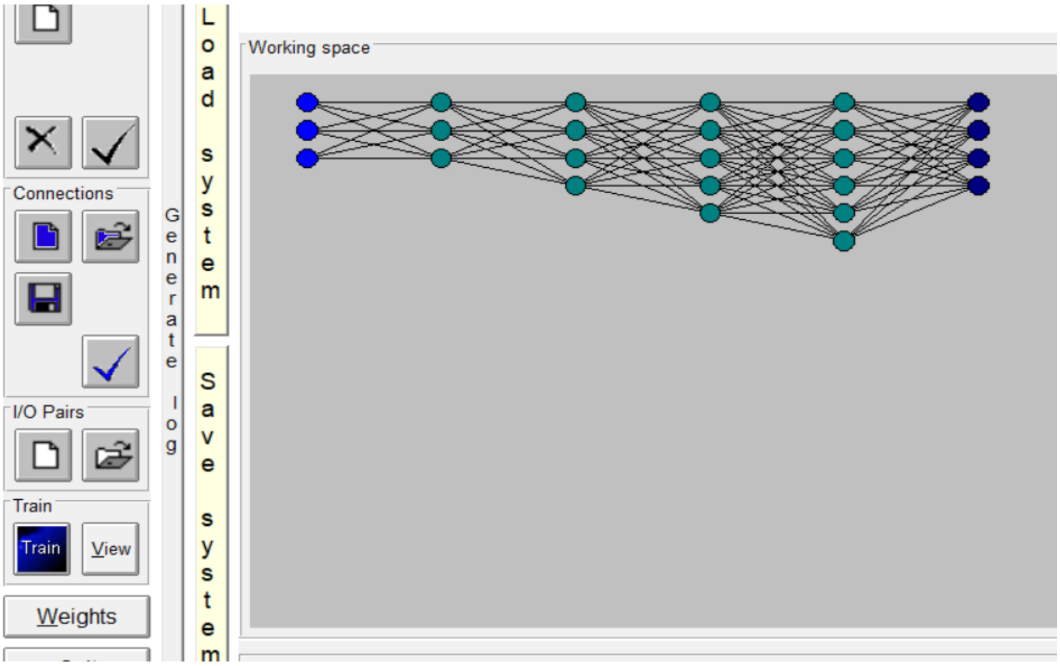

Figure2: Network building stage

The training sets were generated in MS Excel, spanning the range [0, 1] and were normalized. Out of 37 sample examples, 70% were used for training the networks. An artificial neural network (ANN) model with the architecture (3-3-4-5-6-4) was employed. Figure 3 displays the back propagation network screen and the final statistical results from the training stage.

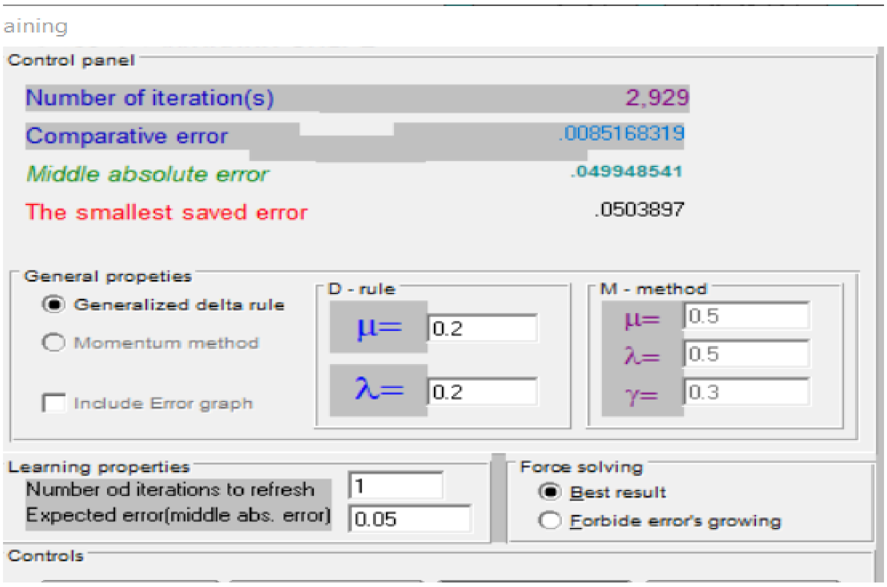

Figure 3: Back propagation neural network

During the testing phase, 30% of the total data sample was used randomly. Figure 4 shows the forecasted values for one of the outputs from the back propagation neural network.

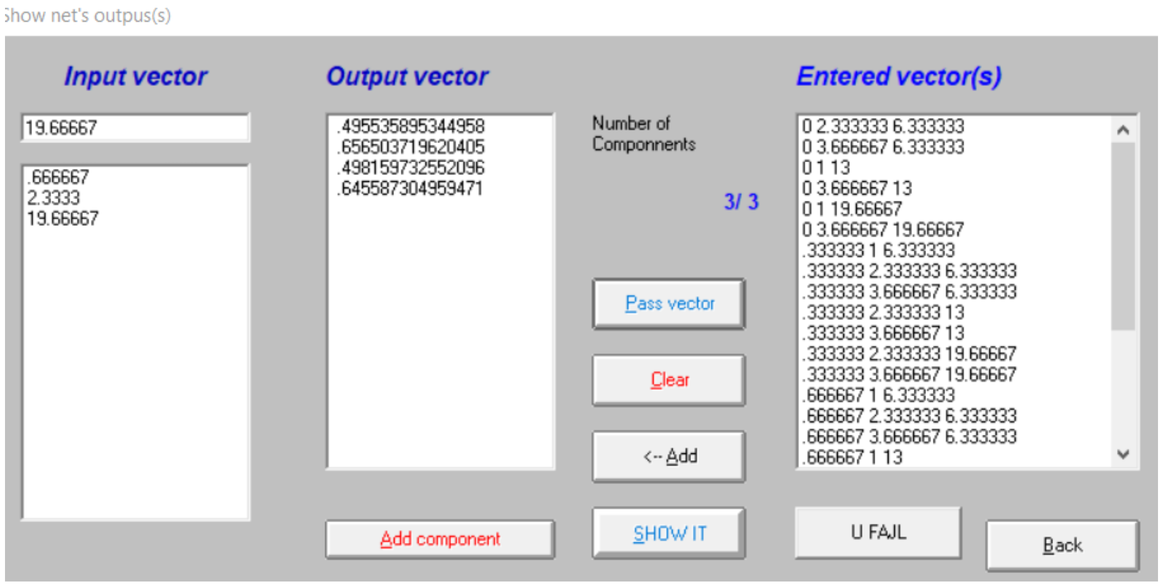

Figure 4: The predicted value of one of the back propagation neural network outputs

Tables 4, 5 and figure (5)show the predicted values of the back propagation neural network outputs compared to the actual data. The results indicate that the Mean Absolute Error (MAE) is very low, demonstrating that the outputs are very close to the target values.

Table 4. Comparison of the forecasted values from the back propagation neural network with the actual data

Input data			Actual outputs				Testing outputs			
X1	X2	X3	Y1	Y2	Y3	Y4	Y1test	Y2test	Y3test	Y4test
0	1	6.3333	0.118	0.25	0.118	0.247	0.116	0.21	0.118	0.21
0	2.3333	13	0.149	0.25	0.149	0.247	0.141	0.25	0.142	0.24
0	2.3333	19.6667	0.281	0.375	0.281	0.369	0.284	0.45	0.284	0.44
0.3333	1	13	0.358	0.5	0.358	0.49	0.38	0.56	0.38	0.54
0.3333	1	19.6667	0.53	0.62	0.53	0.62	0.7	0.8	0.7	0.8
0.6667	2.3333	13	0.252	0.437	0.252	0.429	0.3	0.47	0.3	0.45
0.6667	2.3333	19.6667	0.473	0.625	0.473	0.616	0.49	0.65	0.49	0.64
1	3.6667	13	0.252	0.438	0.252	0.429	0.275	0.44	0.275	0.43
1	3.6667	19.6667	0.4	0.563	0.4	0.556	0.41	0.59	0.42	0.58

Table 5. Square Error and MAE

square Error1	square Error 2	square Error 3	square Error 4
4E-06	0.0016	0	0.001369
6.4E-05	0	4.9E-05	4.9E-05
9E-06	0.005625	9E-06	0.005041
0.000484	0.0036	0.000484	0.0025
0.0289	0.0324	0.0289	0.0324
0.002304	0.001089	0.002304	0.000441
0.000289	0.000625	0.000289	0.000576
0.000529	4E-06	0.000529	0.000001
1E-04	0.000729	0.0004	0.000576
MAE1	MAE2	MAE3	MAE4
0.033666667	0.049111111	0.034444444	0.046111111

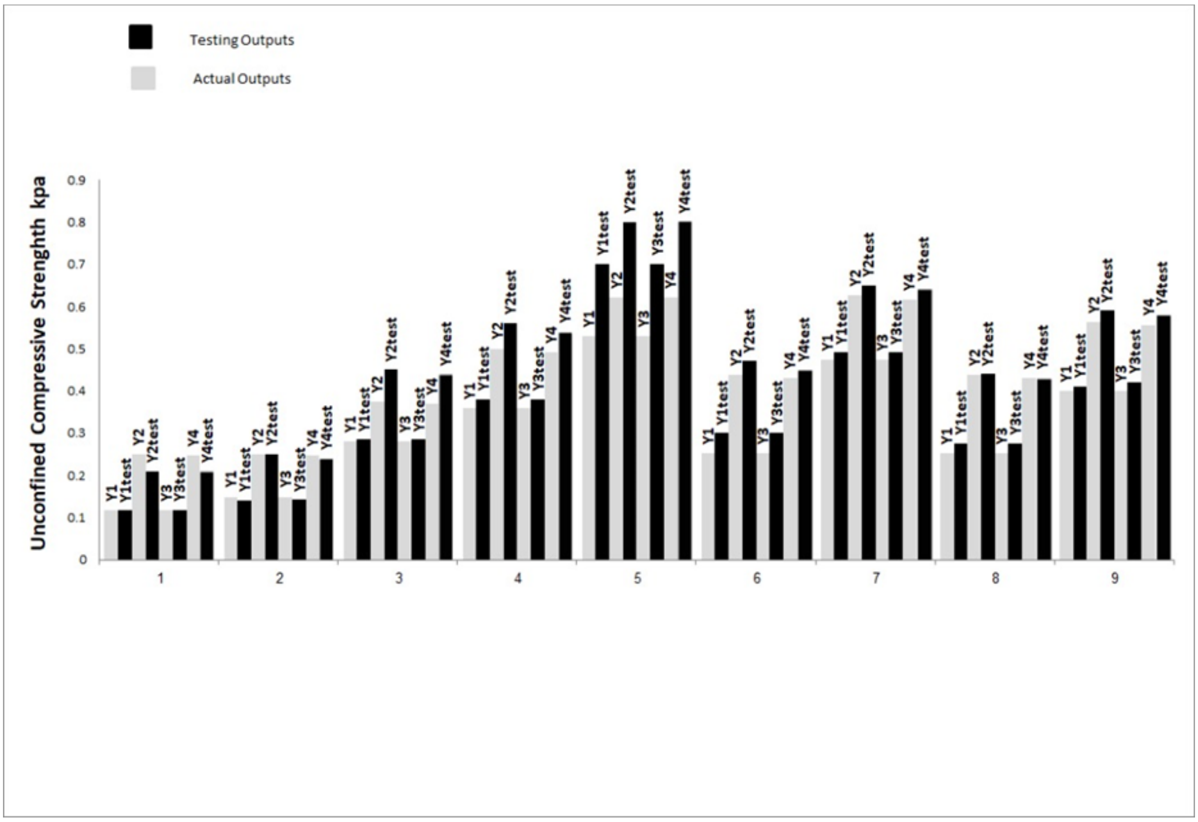

Figure 5: BPN outcome compared with Real data

4. Results and discussion

The results demonstrated that the Back propagation Network (BPNN) effectively predicted the unconfined compressive force. With a model structure of (3 3 4 5 6 4), and learning parameters μ=0.2 and λ=0.2, and an expected error of 0.05, the BPN showed strong predictive capabilities. This effectiveness was confirmed through training and testing, where 70% of the data was used for training and 30% for testing and validation. Additionally, Regression plots for the training and testing data were generated using MATLAB software, as illustrated in Figure 6.

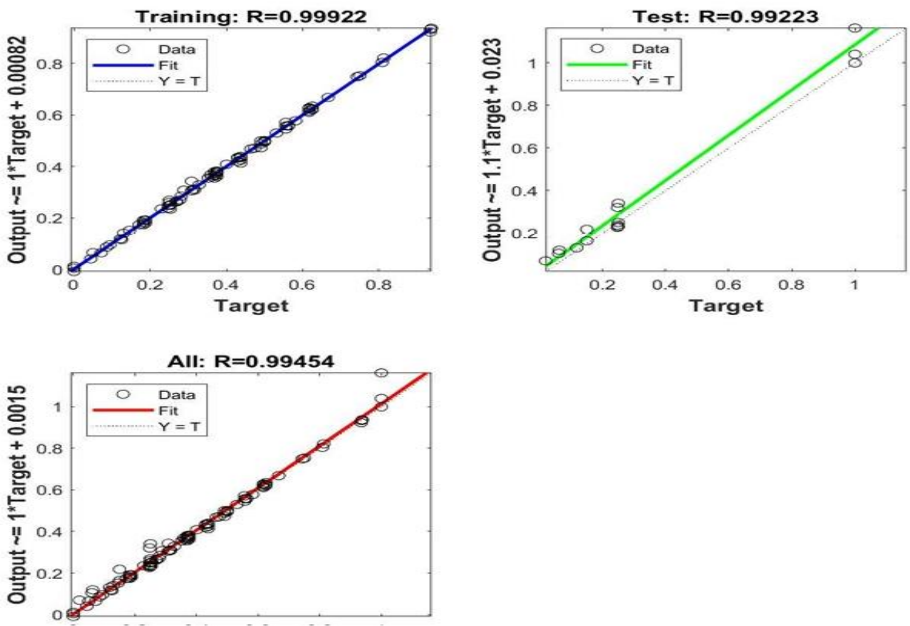

Figure 6: Regression plots of the output with respect to training and testing data

The network outputs are shown as open circles on a plot with targets. A dashed line represents the best linear fit, while a solid line indicates a perfect fit. The correlation coefficient (R-value) measures how well the outputs are explained by the targets. In this case, the R-value is close to 1, indicating a strong correlation and good fit. Figure 6 illustrates that the output closely matches the targets across both training and testing, with an overall R-value of 0.99454. The fit is so close that it is difficult to distinguish between the best linear fit and the perfect fit, demonstrating that the network response is satisfactory.

5. Conclusions

The primary aim of this study was to utilize the Back Propagation Artificial Neural Network (BPNN) approach to predict the unconfined compressive force. From this study, the following key points can be highlighted:

- A BPNN model was effectively developed and utilized to predict the unconfined compressive force within the specified range of input parameters.
- The results indicate that a neural network with the structure (3, 3, 4, 5, 6, and 4) produces desirable outputs with lower expected error compared to other models.

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