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Modeling of Confined Circular Concrete Columns Wrapped by Fiber Reinforced Polymer Using Artificial Neural Network

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ABSTRACT

This study is aimed to explore using an artificial neural network method to anticipate the confined compressive strength and its corresponding strain for the circular concrete columns wrapped with FRP sheets. 58 experimental data of circular concrete columns tested under concentric loading were collected from the literature. The experimental data is used to train and test the neural network. A comparative study was also carried out between the neural network model and the other existing models. It was found that the fundamental behavior of confined concrete columns can logically be captured by the neural network model. Besides, the neural network approach provided better results than the analytical and experimental models. The neural network-based model with R^2 equal to 0.993 and 0.991 for training and testing the compressive strength, respectively, shows that the presented model is a practical method to predict the confinement behavior of concrete columns wrapped with FRP since it provides instantaneous result once it is appropriately trained and tested.

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1. Introduction

The need for seismic retrofitting of concrete structures has led to applying a new material which does not only increase the compressive strength and ductility of concrete members but also possesses other beneficial advantages like light-weight, high tensile strength and modulus, easiness to apply, corrosion resistance, and durability. Fiber-reinforced polymer (FRP) is shown to have these characteristics and has been commonly used for civil infrastructure rehabilitation applications [1–3]. Confining concrete columns is one of the most remarkable uses of FRP Fibers. It is an effective method proved by many engineering applications and experiments [1–7]. Significant research concerning the circular columns retrofitted by FRP has been conducted, and their stress-strain response is predicted by the proposed confinement models having varying degrees of complexity (sophistication). [3–6,8–14].

Early investigations attempted to use FRP confinement analytical models based on models previously used for steel sheet [4,9], but it was soon mentioned that this operation yielded inaccurate and often non-conservative results [15]. Since then, different models particularly suitable for FRP-confined concrete columns, have been proposed [3,5,6,8,10–15]. Many of these models are empirical and have been calibrated against their own sets of experimental data, and some display gross inadequacies when compared to a complete database of experimental results. The failure stress-strain of FRP-confined concrete [4,16,17] is only provided by the most available confinement models, whereas the other models estimate the full stress-strain behavior as bilinear[5,11–14,18]. Most recently, sophisticated rational iterative procedures have been suggested to derive the complete stress-strain response [6]. Accuracy, however, does not necessarily follow complexity (sophistication), and with new confinement models being presented every year, it is far from clear which one(s) should be used in light of the existing test data [19].

It is challenging to apply the statistical approach to a complex nonlinear system due to the considerable technique and experience required to choose the right regression equation. In an attempt to overcome these difficulties, artificial neural networks (ANNs), which provide an alternative method [20,21], are applied in this study. An ANN is a computational tool by which the architecture and internal operational features of the human brain and neuron systems are simulated.

In civil engineering, the methodology of neural networks has been successfully applied to several areas [22–25]. Governing the quantities being modeled by multivariate interrelationships and the available “noisy” or incomplete data are the common features of ANNs successful application. Besides, in developing the neural network model, unlike regression analysis, it is not essential to presume any functional relationship among the different variables. The relationships are automatically constructed by ANNs and adjusted based on the used data for training. [24]. Also, in the future, by adding new results to the training data, it can modify and update its weights automatically and so be able to predict more accurately.

Recently, several studies have been carried out on the prediction of compressive strength of RC members using ANN. Naderpour et al. [26] proposed equations to predict the compressive strength of RC columns strengthened by FRP composites. Cui and Sheikh [27] proposed an analytical model for circular normal- and high-strength RC columns confined with FRP. Their constitutive model used an analytical rupture strain of an FRP jacket for predicting the complete stress-strain curve as well as it accommodated a wide range of concrete strength. Fathi et al. [28] presented an ANN formulation approach to predict compressive strength for concrete cylinders confined with CFRP. This approach represented the effect of CFRP confinement on the ultimate strength of concrete cylinders, which is also provided explicitly in terms of geometrical and mechanical parameters. The good agreement of the proposed ANN model in comparison to experimental results was quite satisfactory. Behfarnia and Khademi [29] conducted a comprehensive study on predicting concrete compressive strength using ANFIS and ANN. They founded that the ANN model was an effective model for the estimation of concrete compressive strength. Naderpour and Alavi [30] proposed a model to predict the shear contribution of FRP in strengthened RC beams using ANFIS. It was concluded that their proposed model provides an accurate and reliable tool than the guidelines equations. Hosseini [31] developed an ANN model based on a genetic algorithm to predict the capacity of RC beams retrofitted by FRP. The results showed that the shear capacity of the considered beams could be predicted by the proposed ANN model based on a genetic algorithm. Sharifi et al. [32] used the ANN method to investigate the estimation of the compressive strength of rectangular concrete columns confined by FRP. The results demonstrated that the proposed model based on ANN gave the best accuracy than the other models and conducted a sensitivity analysis based on Garson's algorithm on indicating the value of used variables. Khan et al. [33] developed a stress-strain model to estimate the strength and strain enhancement ratio of FRP tube confined concrete cylinders under axial compression by implementing ANN. The predictions of the developed models had a good agreement with the experimental investigation results of the compiled database. Naderpour et al. [34] presented an ANFIS model to predict the ultimate strength of FRP-confined circular RC columns. The obtained results of the ANFIS model were compared with results from other models. The highest accuracy to predict the experimental results was observed in the ANFIS model. As can be seen there is no study about the modeling of confined circular concrete columns wrapped by fiber-reinforced polymer using an artificial neural network. For this purpose, In this study, the possibility of using artificial neural networks (ANNs) in predicting the compressive strength of confined concrete circular columns and corresponding strain by using valid results from past experiments is explored. Because of the comparatively scarce test data now presented on the square and rectangular, slender, and eccentrically loaded columns, this paper deals only with FRP-wrapped circular columns under concentric axial load. Since the ability of the previous confinement models to predict behavior is somewhat dependent on whether the confinement is provided by an FRP wrap or tube [35], and so the focus of this study on comparison purposes is on the wrapped-columns.

2. Fundamental concepts of artificial neural network

An ANN performs as a network by a set of simple processing units called neurons that interact with each other through weighted connections. As can be seen in figure 1, The function of a neuron is estimated by a processing element.

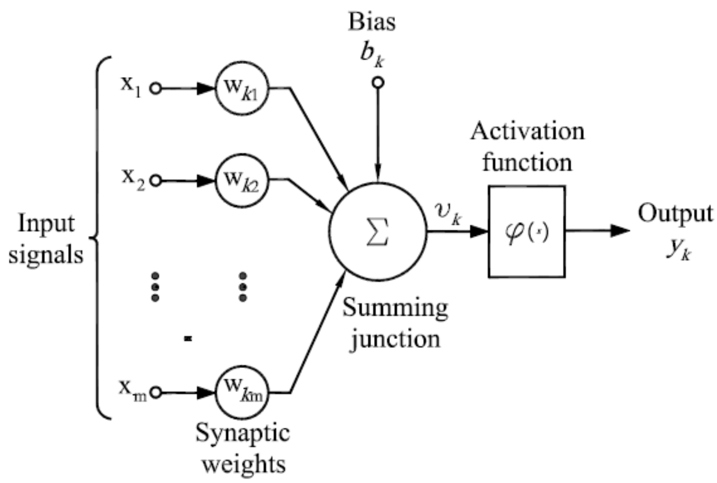

Fig. 1. Model of a neuron [36].

The processing units may be arranged logically into two or more layers called input, hidden, and output layers, shown in Figure 2. The topology or architecture of an ANN is similar to that of the brain and nervous system; each neuron can have many inputs but only one output. However, each output branches out to the input of many other processing elements [22]. Receiving input from its neighboring units, which provides incoming activations, computing, and output, and also sending the output to its neighbors, are the main duties of processing units. A set of weights can affect the magnitude of the input being received by the neighboring units and also provide the strength of the connections among the processing units. The output processing units produce output compared to the target output data, and the weights are properly modified or adjusted based on training or learning rule. The output produced by the output processing units is compared to the target output data, and the weights are appropriately modified or adjusted based on training or learning rule. Finally, by learning the problem, a stable set of weights adaptively evolves, which will produce good results.

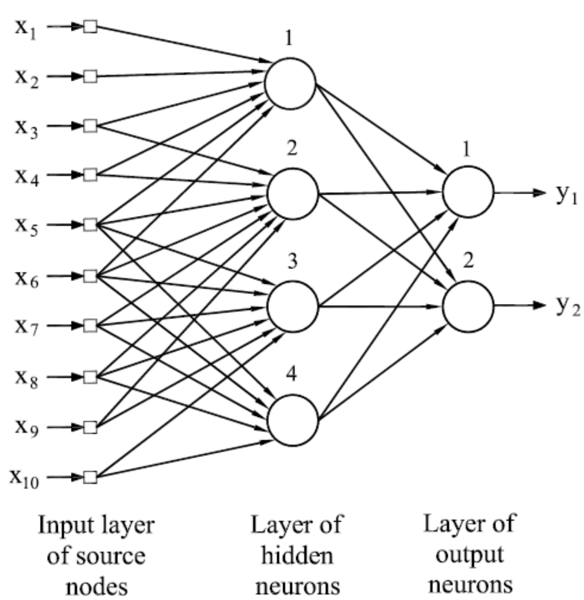

Fig. 2. The topology of a neural network with one hidden layer [35].

ANN, like structure based on the biological nervous system, represents a surprising number of characteristics, e.g., learn from experience, and generalize from previous examples to new problems by inferring solutions through problems beyond those they are exposed to due to training, process information rapidly [37].

Parker and Werbos independently discovered the Back-propagation learning method. Rumelhart et al. generalized and developed this method to a workable process.

In back-propagation, learning is accomplished by propagating a set of input training patterns through a network consisting of an input layer, one or more hidden layers, and an output layer. Each layer has its corresponding units and weight connections. The calculated outputs at the output layer are subtracted from the desired (target) output, and the error is obtained by the squared sum of the output difference. This measurement represents the level at which the network has learned the input-output data and may be used to determine the gradient of the learning procedure [22].

Determining the connection weight matrices and the layout of the connections and also the application of the learning rule by which the neural network obtains the desired relationship embedded in the training data are primarily involved in the learning process. An error criterion is usually selected for the network output, and the simulation can be terminated by setting the maximum number of cycles [24].

The error will approach a minimum value if the network "learns." After the training phase, the ANNs can be tested for other input data where the final values of the weights obtained in the training phase are used. No weight modification is involved in the testing phase. Details of the BPN algorithm and its variants can be found in the literature [38].

Aiming at empirically validating the performance of an ANN model which has been trained by presenting it with a set of training patterns, the reliability, and accuracy of the network performance is evaluated via a selected error matric based on data (referred to as test data), which was not in training. An ANN prediction model can be evaluated and validated by common error methods like root mean squared error (RMSE) or the mean absolute error (MAE).

3. Behavior and models of confined circular concrete columns with FRP

A concrete cylinder confined by FRP jacket starts expanding laterally when subjected to axial compressive stress. The FRP jacket loaded in tension in the hoop direction can limit and decrease the expansion. The FRP jacket provides confining pressure, which is continuously increased, whereas the lateral strain of concrete increases due to the linear elastic stress-strain behavior of FRP, in contrast to steel-confined concrete in which the confining pressure remains constant even when the steel is in the plastic range [7]. Figure 3 describes the stress-strain behavior of the confined concrete column. Confinement acts as passive in concrete and only is effective once the internal cracking increases the volume. Passive confinement enhances the compressive strength of the concrete and increases its ductility [24].

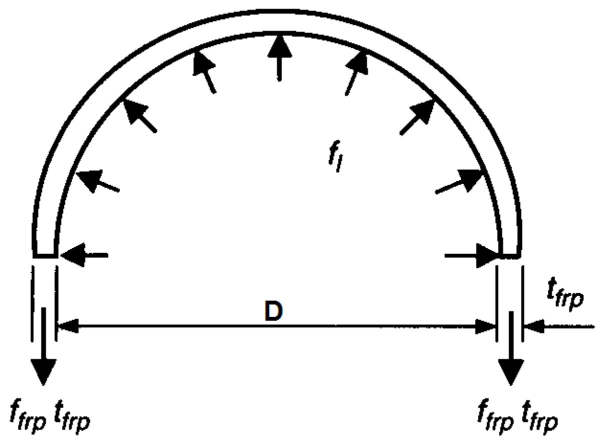

Fig. 3. Applying confinement pressure to the concrete core.

Various analytical and empirical models have been proposed to estimate the compressive strength, f'_{cc}, and corresponding strain, ε_{cc}, of confined concrete columns considering various parameters [3–6,8–14]. To compare the results obtained from the neural network model, some remarkable methods are selected and used in this study are outlined in the following. A detailed discussion was carried out in the literature on the accuracy and comparison of the existing models [7,19,35]. To ensure uniformity of notation withing the current paper, The notation and format of the original equations have been modified in most cases. In the following expressions, P_u represents the ultimate confining pressure applied by an FRP wrap. For a circular concrete column of diameter D, confined by a circumferential wrap with tensile strength, $f_{fu,}$ and thickness, nt, this pressure is computed by assuming the failure of concrete when the wrap reaches its failure stress [14]. Thus, an expression giving the lateral confining pressure at the ultimate level can be obtained using the equilibrium of forces (Figure 3).

$$P = E_L.\varepsilon_L = E_L.\varepsilon_{frp} \tag{1}$$

$$E_L = \frac{2E_{frp}.t_{frp}}{D} \tag{2}$$

$$P_u = \frac{2f_{frp}.t_{frp}}{D} \tag{3}$$

Where E_L is the confinement modulus or lateral modulus.

As for the strength enhancement, almost all models relate $f'_{cc}/\ f'_{co}$ to the $P_u/\ f'_{co}$ ratio, except for the Kono model [9], which expresses $f'_{cc}/\ f'_{co}$ only as a function of P_u, Samaan et al. [12], expressed $f'_{cc}/\ f'_{co}$ as a function of P_u and f'_{co}, and Xiao and Wu [13], included the ratio $f'^2_{co}/\ E_L$ as a significant variable. The ductility enhancement, as expressed by the ratio $\varepsilon_{cc}/\varepsilon_{co}$, appears to be related not just to the strength properties but also to the stiffness of the confining device. Some of the most important models to predict the compressive strength of confined concrete used in this study are presented in Table 1.

Table 1
Models of predicting compressive strength of confined concrete.

Author	Equation	Ref
Fardis and Khalili	$f'_{cc}/f'_{co}=1+2.05(f_l/f'_{co})$	[4]
Saadatmanesh et al.	$f'_{cc}/f'_{co}=\left[-1.254+2.254\sqrt{1+\frac{7.94 f_l}{f'_{co}}}-2\frac{f_l}{f'_{co}}\right]$	[9]
Miyauchi et al.	$f'_{cc}/f'_{co}=1+2.98(f_l/f'_{co})$	[5]
Samaan et al.	$f'_{cc}/f'_{co}=1+6(f_l^{0.7}/f'_{co})$	[12]
Toutanji	$f'_{cc}/f'_{co}=1+2.3(f_l/f'_{co})^{0.85}$	[11]
Saafi et al.	$f'_{cc}/f'_{co}=1+2.2(f_l/f'_{co})^{0.84}$	[3]
Karbhari and Gao	$f'_{cc}/f'_{co}=1+2.1(f_l/f'_{co})^{0.87}$	[14]
Lam and Teng	$f'_{cc}/f'_{co}=1+2(f_l/f'_{co})$	[18]

4. Experimental data

Comprehensive information about the feature of the behavior of the materials should be included in a good training data set. Therefore, the trained neural network will contain sufficient information to qualify as a material model. Results of about 187 tests from 18 different experiments set documented in the published literature were collected.

Although considering the effects of quality parameters in neural networks is possible by designating numeric variables to them, but in this study, like other existing models, a specific type of leg was considered Filament wound, wrap, and tube and fiber type (e.g., AFRP, CFRP, and GFRP) are as variables. The ANN model was trained for CFRP wrapped columns. The previous researchers just took into account the diameter of the cylinder, D in the prediction models, and the height of the cylinder, H was not considered, whereas size effect is a relevant issue that needs specific investigations. Therefore, in this study, to exclude size effect, the experiment data limited to those which have reported the H/D ratio equal to 2.

Some authors had reported the experimental results with identical properties that are impossible for a neural network to learn those patterns with the same inputs and different outputs. Therefore, to prevent falling in this loop, the results of identical specimens were averaged. Eventually, 58 sets out of 180 gathered sets from 9 published literatures [5,10,39–44] were selected, which are presented in Table 2. These ranges are listed in Table 3 (At first, 187 datasets were collected from valid references, Then, out of 187 data, 58 homogeneous data were selected, and heterogeneous data were deleted).

Table 2
Initial Experimental Data as the input of the ANN model.

Reference	Code	D (mm)	nt (mm)	E_f (MPa)	f_{fu} (MPa)	f'_{co}(MPa)	ε_{co} (%)	f'_{cce} (MPa)	ε_{cce} (%)	f'_{ccp} (MPa)	ε_{ccp} (%)
Harmon et al.,1992	HA1	51	0.089	235000	3500	41	0.23	86	1.15	84.281	1.191
	HA2	51	0.179	235000	3500	41	0.23	120.5	1.57	109.060	1.551
	HA3[a]	51	0.344	235000	3500	41	0.23	158.4	2.5	166.003	2.358
	HA4	51	0.689	235000	3500	41	0.23	241	3.6	239.774	3.546
	HA5	51	0.179	235000	3500	103	0.4	131	1.1	130.165	1.079
	HA6[a]	51	0.344	235000	3500	103	0.4	193.2	2.05	190.262	1.842
	HA7	51	0.689	235000	3500	103	0.4	303.6	3.45	302.877	3.449
Picher et al.,1996	PI1	153	0.36	83000	1266	39.7	0.25	55.98	1.07	59.175	1.016
Watanabe et al.,1997	WA1	100	0.1675	223400	2728.5	30.2	0.25	46.6	1.511	54.517	1.426
	WA2	100	0.5025	223400	2728.5	30.2	0.25	87.2	3.108	90.247	3.193
	WA3	100	0.67	223400	2728.5	30.2	0.25	104.6	4.151	100.573	4.047
	WA4	100	0.14	611600	1562.7	30.2	0.25	41.7	0.575	40.056	0.576
	WA5[a]	100	0.28	611600	1562.7	30.2	0.25	56	0.876	50.342	0.886
	WA6	100	0.42	611600	1562.7	30.2	0.25	63.3	1.298	63.535	1.298
Miyauchi et al.,1997	MI1	150	0.11	230500	3481	45.2	0.219	59.4	0.945	66.811	0.789
	MI2[a]	150	0.22	230500	3481	45.2	0.219	79.4	1.245	82.268	1.071
	MI3	150	0.11	230500	3481	31.2	0.195	52.4	1.213	52.578	1.291
	MI4	150	0.22	230500	3481	31.2	0.195	67.4	1.554	60.585	1.584
	MI5	150	0.33	230500	3481	31.2	0.195	81.7	2.013	68.754	1.917
	MI6	100	0.11	230500	3481	51.9	0.192	75.2	0.956	78.461	0.758
	MI7[a]	100	0.22	230500	3481	51.9	0.192	104.6	1.275	113.373	1.230
	MI8	100	0.11	230500	3481	33.7	0.19	69.6	1.406	58.712	1.209
	MI9	100	0.22	230500	3481	33.7	0.19	88	1.488	68.772	1.493
Kono et al.,1998	KO1,2	100	0.167	235000	3820	34.3	0.17	61.15	0.9475	58.085	1.009
	KO3,4,5	100	0.167	235000	3820	32.3	0.234	59.23	1.07	53.271	1.056
	KO6,7,8	100	0.334	235000	3820	32.3	0.234	66.73	1.75	70.693	1.503
	KO9,10	100	0.501	235000	3820	32.3	0.234	88.5	1.62	85.391	1.928
	KO11,12,13	100	0.167	235000	3820	34.8	0.229	54.7	0.989	59.450	1.001
	KO14,15[a]	100	0.334	235000	3820	34.8	0.229	82.05	2.06	84.221	1.520
	KO16,17	100	0.501	235000	3820	34.8	0.229	106.7	2.425	105.693	2.023
Matthys et al., 1999	MA1	150	0.117	220000	2600	34.9	0.21	46.1	0.9	46.101	0.894
	MA2[a]	150	0.235	500000	1100	34.9	0.21	45.8	0.6	32.848	0.400
Shahawy et al.,2000	SH1	153	0.36	82700	2275	19.4	0.2	33.8	1.59	36.723	1.620
	SH2	153	0.66	82700	2275	19.4	0.2	46.4	2.21	48.110	2.023
	SH3	153	0.9	82700	2275	19.4	0.2	62.6	2.58	62.674	2.594
	SH4[a]	153	1.08	82700	2275	19.4	0.2	75.7	3.56	73.213	3.047
	SH5	153	1.25	82700	2275	19.4	0.2	80.2	3.42	80.739	3.359
	SH6	153	0.36	82700	2275	49	0.2	59.1	0.62	58.250	0.582
	SH7	153	0.66	82700	2275	49	0.2	76.5	0.97	76.804	0.923
	SH8	153	0.9	82700	2275	49	0.2	98.8	1.26	94.713	1.339
	SH9	153	1.08	82700	2275	49	0.2	112.7	1.9	111.606	1.805
Micelli et al.,2001	MC5,6,7,8[a]	100	0.16	227000	3790	37	0.19	59.5	1.015	58.357	0.834
Rousakis,2001	RO1,2,3	150	0.169	118340	2024	25.15	0.32	41.48	1.37	39.558	1.335
	RO4,5,6	150	0.338	118340	2024	25.15	0.32	59.21	2.017	54.312	1.896
	RO7,8,9	150	0.507	118340	2024	25.15	0.32	68.15	2.423	67.774	2.470
	RO10,11,12[a]	150	0.169	118340	2024	47.44	0.31	67.617	0.853	68.977	0.875
	RO13,14	150	0.338	118340	2024	47.44	0.31	82.355	1.335	83.805	1.190
	RO16,17,18	150	0.507	118340	2024	47.44	0.31	95.755	1.683	94.426	1.452
	RO19,20,21	150	0.169	118340	2024	51.84	0.29	78.915	0.67	74.882	0.822
	RO22,23,24	150	0.338	118340	2024	51.84	0.29	90.475	1.02	90.038	1.106
	RO25,26,27[a]	150	0.507	118340	2024	51.84	0.29	110.463	1.33	101.137	1.338
	RO28,29,30	150	0.845	118340	2024	51.84	0.29	125.76	1.555	117.587	1.772
	RO31,32,33	150	0.169	118340	2024	70.48	0.35	84.847	0.707	86.694	0.595
	RO34,35,36[a]	150	0.338	118340	2024	70.48	0.35	99.797	0.9	102.534	0.825
	RO37,38,39	150	0.507	118340	2024	70.48	0.35	110.857	1.16	118.436	1.063
	RO40,41,42	150	0.169	118340	2024	82.13	0.31	95.837	0.477	86.890	0.484
	RO43,44,45	150	0.338	118340	2024	82.13	0.31	98.173	0.44	99.865	0.673
	RO46,47,48	150	0.507	118340	2024	82.13	0.31	124.713	0.95	115.013	0.897

Table 3
Statistic Properties of Training and Testing Sets for the ANN model.

Input and Output Variables		D (mm)	H (mm)	nt (mm)	E_f (MPa)	f_{fu} (MPa)	f'_{co} (MPa)	f'_{cc} (MPa)	f'cc (%)
All Data	Ave.	123.05	245.93	0.39	198917.9	2707.89	44.26	88.23	1.56
	Min.	51	102	0.089	82700	1100	19.4	33.8	0.44
	Max.	153	305	1.25	611600	3820	103	303.6	4.151
	Standard Deviation	35.44	70.72	0.27	123592.9	809.82	20.68	46.29	0.86
Training Set	Ave.	124.6	249	0.3983	186846	2706	43.48	86.63	1.57
	Min.	51	102	0.089	82700	1266	19.4	33.8	0.44
	Max.	153	305	1.25	611600	3820	103	303.6	4.151
	Standard Deviation	34.78	69.39	0.2804	111888	775.1	20.56	47.34	0.87
Test Set	Ave.	117.1	234.1	0.35	245193	2715.14	47.26	94.38	1.52
	Min.	51	102	0.16	82700	1100	19.4	45.8	0.6
	Max.	153	305	1.08	611600	3820	103	193.2	3.56
	Standard Deviation	38.86	77.63	0.25	158095	969.75	21.77	43.43	0.86

5. Application of ANN to FRP confined concrete

Examining the input variables given in the references above can help to select those parameters for a network model. In general, the following six parameters were concluded in almost all models for prediction of peak axial stress of FRP confined concrete specimen, f'_{cc}, and corresponding strain at peak stress, ε_{cc}. The six major variables that are used as input nodes in the ANN model are listed as follows:

D = Diameter of the concrete cylinder

nt = total thickness of the applied FRP

E_f = FRP modulus of the elasticity

f_{fu} = FRP ultimate tensile strength

f'_{co} = peak stress of an unconfined concrete cylinder

ε_{co} = strain corresponding to peak stress of an unconfined concrete cylinder

Having the above six input nodes, the two output nodes correspond to maximum axial stress, f'_{cc}, and strain, ε_{cc}, of FRP confined concrete, respectively. The data for 58 columns from the experiments of Miyauchi et al. [5], Kono et al. [10], Harmon and Slattery [39], Watanabe et al. [40], Micelli et al. [41], Matthys et al. [42], Shahawy et al. [43], Rousakis [44], were grouped randomly into training and test data. Forty-six (46) data patterns were used as training data, and the remaining twelve (12) data patterns were regarded as test data.

In this study, a scientifically available program widely used by researchers during the last decade was applied for the simulations. The program neural works professional II plus “NW II” [45] is a multi-paradigm neural network prototyping and development tool which is provided with powerful diagnostic instruments, such as the root–mean square error (RMSE), network weights, classification rate, and confusion matrices, for monitoring the network instantly to achieve a better understanding of the network performance. Once the network is trained and converged, a test set is presented to the network sequentially to verify the reliability and accuracy of the network performance. Considering the number of training patterns and aiming at reaching the desired performance and accuracy of the network, different architecture for the network is assumed, trained, and then the best will be selected. The best architecture is the one that gives the nearest predictions to both training and test sets [22].

In this study, the network configuration was obtained once the performance of various configurations for a fixed number of cycles was monitored. Then, learning parameters were changed, and learning processes were reported. To yield the best results, two hidden layers with five neurons in the first hidden layer, and three neurons in the second hidden layer were selected. Transfer functions were “tangent hyperbolic” and linear for the hidden and output layers, respectively. Moreover, to avoid over-training, the convergence criteria for stopping the training network were:

- Root Mean Square Error (RMSE) of 0.01 for normalized data;
- Maximum cycles of 50000

Whereas the error tolerance was not achieved, the simulation stopped when the maximum number of cycles was reached. In the NW II program, by choosing “Extended Delta-Bar-Delta” (Ext DBD) as the learning rule, the program sets the following parameters Momentum, Learning Coefficient Ratio, and f’ offset automatically.

Since tangent hyperbolic transfer function is asymptotic to values -1 and 1, the derivative at or close to values -1 and 1 will approach zero, producing a minimal signal error, which leads to slow learning. The input and output data were scaled into the interval [-0.9, 0.9] and the interval [-0.8, 0.8], respectively, to avoid the slow rate of learning near the endpoints, particularly of the output range.

When the network is trained, it is presented by the test data to assess the accuracy of the model. Tables 4 and 5 show the comparison of the performance of the proposed models for RMSE and R^2, both for training and test data. It can be seen that the BPN model has the best results. To obtain the maximum strength of confined concrete by the BPN, the values of RMS error are 5.558 MPa for the training set and 6.191 MPa for the testing set; while for the corresponding strain of confined concrete, the values of RMS error are 0.127 and 0.246 for the training set and testing set respectively, which are the lowest values among the prediction models. Moreover, the R^2 can be used as an index to indicate how well the considered independent variables (D, nt, f_{fu} ,E_f, f'_{co}, and ε_{co}) justify the measured dependent variables (f'_{cc} and ε_{cc}) and, subsequently, the accuracy of the trained network. All values of R^2 were found to be greater than 0.983 for the training set and testing set, which represents a significant correlation between the independent variables and the measured dependent variables.

Table 4
Summary of the Errors of BPN Model for strength.

f'_{cc}	*Max E.*	*Min E.*	*MAE*	*RMS*	R^2	*COV*	*STDV*	*AVG*
Training Set	19.227	0.00125	3.968	5.558	0.993	0.076	0.078	1.021
Testing Set	12.952	1.142	5.001	6.191	0.991	0.121	0.125	1.036

Table 5
Summary of the Errors of BPN Model for strain.

f'cc	*Max E.*	*Min E.*	*MAE*	*RMS*	R^2	*COV*	*STDV*	*AVG*
Training Set	0.40100	0.00050	0.09500	0.127	0.989	0.105	0.107	1.021
Testing Set	0.539	0.0089	0.176	0.246	0.983	0.139	0.158	1.138

6. ANN model simulation

A neural network model uses the training examples to learn and construct relationships between the input and output parameters. Due to the scarce and limited training data, it is expected that the trained model may not be able to capture the complicated interrelationships among physical parameters completely. Therefore, it is necessary to validate the performance of the ANN model in simulating the behavior of physical processes. This can be accomplished through testing the model with hypothetical data by changing the values of some input parameters. In the parametric study, two types of columns were used; the M column which has the properties like the Miauchi [5] specimens used in his experiment (i.e. D=150 mm, nt= 0.11,0.22,0.33 mm, E_f=230500 MPa, f_{fu}=3481 MPa, f'_{co}=31.2,33.7,51.9 MPa, and ε_{co}=0.195%) and S column which is identical to Shahawy [35] specimens (i.e. D=153 mm, nt= 0.36,0.66,0.9,1.08,1.25 mm, E_f=82700 MPa, f_{fu}=2275 MPa, f'_{co}=19.4,49 MPa, and ε_{co}=0.2%). In the M column, the thickness of the wrapped FRP, nt, that is one of the most important parameters in confinement, is varied from 0.1 mm to 1 mm for unconfined concrete stresses, $f'_{co,}$ equal to 30, 40, and 50 MPa with keeping constant the other parameters. Similarly, in the S column, considering constant values for the variables above, like in the M column, the thickness is varied from 0.35 mm to 1.25 mm for unconfined concrete stresses equal to 17, 34, and 51 MPa. For the M column, as it was expected and shown in Figure 4 and Figure 5, the network revealed an increasing linear trend in the interval 0.1 to 0.3 for the thickness, which are the ranges of learning patterns but nonlinear for those patterns out of training set ranges. In contrast, for the S column, which the range of varying thicknesses is the same as the range that the model was trained for, the trend of predictions is ever-increasing, and the model does not need to predict values out of its training ranges. Hence, it is observed that the ANN model is able to predict the values in its learning patterns regions but poorly in the values out of it.

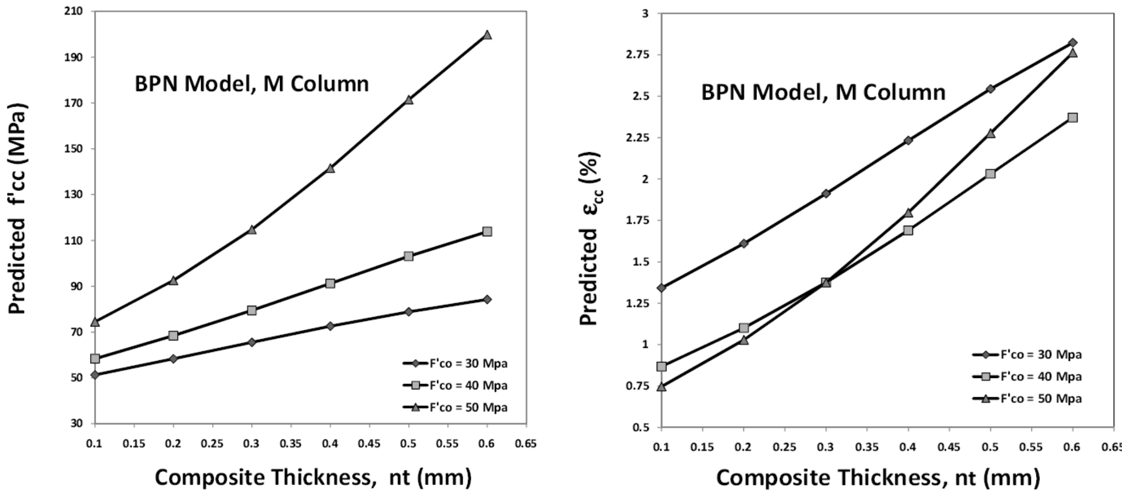

Fig. 4. Predictions of the ANN Model for Mcolumn

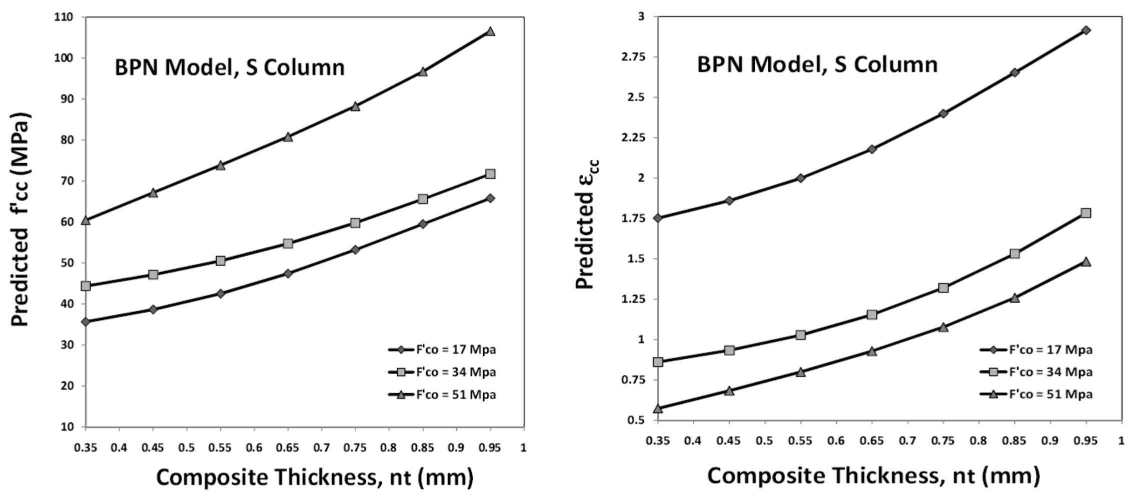

Fig. 5. Predictions of the ANN Model for S column

7. Discussion and comparison of prediction models

The training and testing data for calculating the predicted maximum strength, f'_{ccp}, and corresponding strain, ε_{ccp}, of confined concrete columns are used to compare the neural network results with other well-known existing models. Since different models may involve different parameters, the comparison is made by plotting experimental values versus predicted values, with a 45-degree line corresponding to perfect agreement between predictions and experimental results (i.e., $\varepsilon_{cce}/\varepsilon_{ccp}=1$ and $f'_{cce}/f'_{ccp}=1$). As shown in Figure 6 for f'_{cce} versus f'_{ccp} and Figure 7 for ε_{cce} versus ε_{ccp}, points falling in the upper part of the graph show conservative predictions, while points falling down the line are obtained from theoretical values being higher than the experimental ones. Figure 6 and Figure 7 clearly show that the least scattered data around the diagonal line confirms that the neural network-based model is an excellent predictor for the values of f'_{cc} and ε_{cc}, respectively (Because the predictions (points) are closer to the laboratory values (45-degree line) compared to other models).

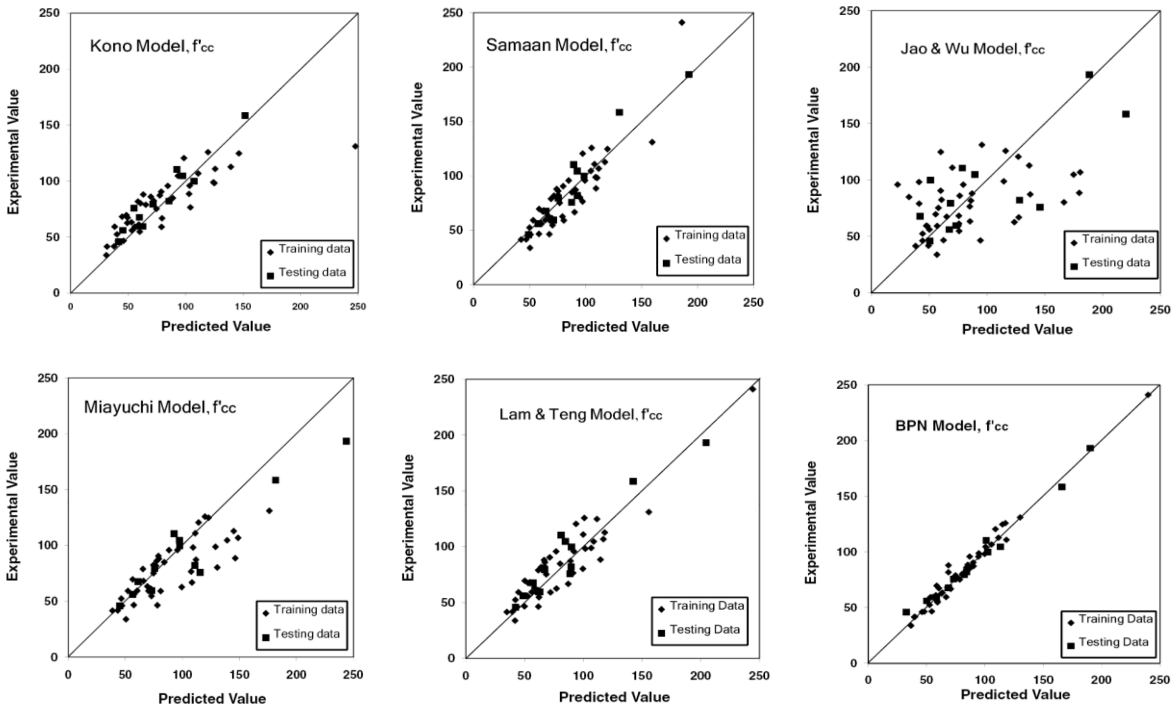

Fig. 6. Comparison of the models in predicting f'cc

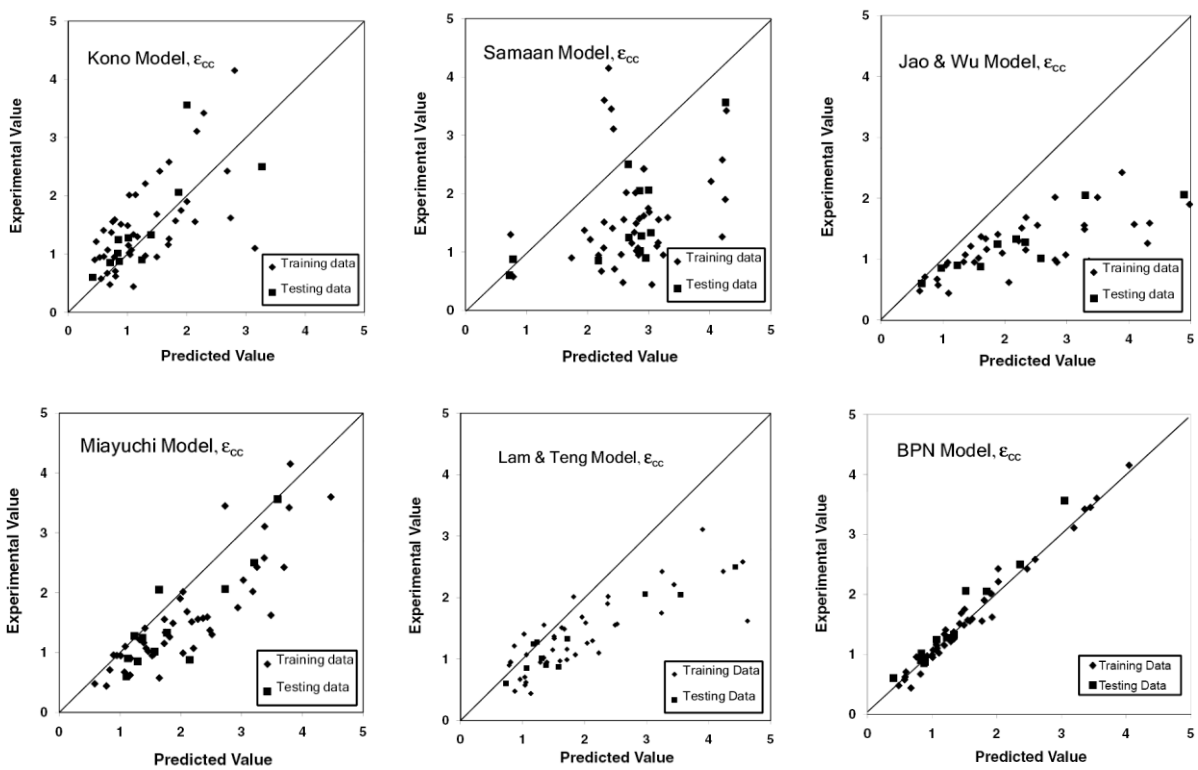

Fig. 7. Comparison of the models in predicting ε_{cc}.

Also, the Figs. 6 and 7 shows that Xiao and wu model has the highest deviation in predicting compressive strength among other models while in term of strain this model and Samaan model has the highest deviation. These figures also show that the models are more accurate in predicting compressive strength compared to strain.

While the correlation between the values of experimental and predicted from previous models is more scattered. The values of RMSE (Root Mean Square Error) and R^2 (Absolute Fraction of Variance) of the training and testing results for the prediction models are also listed in Table 6 based on the following equations for comparison purposes.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(f'_{cc(experimental)} - f'_{cc(predict)}\right)^2}{\sum_{i=1}^{N}\left(f'_{cc(experimental)} - \overline{f'}_{cc(experimental)}\right)^2} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}(f'_{cc(predict)} - f'_{cc(experimental)})^2} \tag{5}$$

It can be observed that the smallest RMSE and the largest R^2 (closest to 1) for both the training and testing sets are derived by the BPN model. The large deviation for the analytical models shows that the analytical models performed well for their test data but poorly on other data. Moreover, the prediction models have been compared using the average value (AVG), standard deviation (STD), and coefficient of variation (COV) of the ratio of f'_{cce}/f'_{ccp} and $\varepsilon_{cce}/\varepsilon_{ccp}$. Table 6 indicates that for the ratios of f'_{cce}/f'_{ccp}, the neural network model possesses the least COV value of 7.6% (with AVG= 1.021 and STD= 0.098) and 12.1% (with AVG= 1.036 and STD= 0.125) for the training and testing sets, respectively. Similarly, for the ratios of $\varepsilon_{cce}/\varepsilon_{ccp}$, the ANN model possesses the least COV value of 10.4% (with AVG= 1.021 and STD= 0.107) for the training set and 13.9% (with AVG= 1.138 and STD= 0.158) for testing set. It is seen that the predictions of the ANN model, even for test data, are relatively better than the results of analytical models. The performance of the ANN model is improved by an increase in the number and distribution of the training database.

The maximum error is related to the Kono model and equal to 356.6 for training data, while the minimum error is related to BPN, Miayuchi, and Kono models and equal to 0 for training data. The lowest R^2 is for Karbahari & Gao model and related to strain prediction.

8. Conclusions

This study showed the application of the neural network method for predicting the complex nonlinear behavior of concrete columns confined with FRP wraps. It is not possible to propose an ANN model that is used for columns with a broad range of values as input parameters due to the data limitation.

Table 6
Statistic results for the prediction models.

Statistic		Maximum Error		Minimum Error		Mean Absolute Error		Root Mean Square Error (RMSE)		R^2		Coefficient of Variance		Standard Deviation		Average	
		Train Set	Test Set	Train Set	Test Set	Train Set	Test Set	Train Set	Test Set	Train Set	Test Set	Train Set	Test Set	Train Set	Test Set	Train Set	Test Set
Fardis	$f'cc_{(Richart)}$	187.7	103.4	0.249	1.481	35.38	31.93	54.29	47.1	0.934	0.925	0.239	0.22	0.185	0.177	0.773	0.806
	$f'cc_{(Newman)}$	153.5	104.7	1.026	2.371	32.34	30.18	44.1	42.06	0.952	0.948	0.196	0.171	0.15	0.135	0.761	0.79
	ε_{cc}	3.851	3.33	0.127	0.368	1.301	1.247	1.522	1.499	0.162	-0.042	0.524	0.642	3.145	3.74	6.001	5.831
Saadatmanesh	$f'cc$	85.65	83.29	0.033	0.235	19.98	18.86	26.5	28.36	0.904	0.935	0.182	0.138	0.152	0.118	0.838	0.86
	ε_{cc}	1.749	1.719	0.018	0.136	0.58	0.593	0.698	0.727	0.851	0.83	0.285	0.243	0.214	0.181	0.752	0.742
Miayuchi	$f'cc$	81.82	50.52	0.118	0.275	18.45	16.19	26.78	22.58	0.95	0.944	0.201	0.175	0.183	0.165	0.91	0.944
	ε_{cc}	1.865	1.269	0	0.034	0.567	0.452	0.693	0.559	0.861	0.873	0.252	0.287	0.19	0.227	0.757	0.793
Kono	$f'cc$	356.6	188	0.56	3.172	22.61	23.75	56.11	55.17	0.919	0.9	0.225	0.203	0.239	0.213	1.064	1.05
	ε_{cc}	7.542	3.639	0	0.014	0.722	0.647	1.323	1.181	0.629	0.564	0.447	0.344	0.548	0.381	1.227	1.108
Samaan	$f'cc$	55.66	28.27	0.117	1.067	12.23	9.149	16.46	12.35	0.947	0.96	0.162	0.129	0.158	0.131	0.975	1.015
	ε_{cc}	3.066	2.053	0.21	0.096	1.456	1.065	1.57	1.257	0.168	0.697	0.638	0.421	0.386	0.265	0.605	0.628
Tutanji	$f'cc$	134.7	95.58	2.261	0.152	28.76	26.53	39.19	37.59	0.954	0.951	0.189	0.162	0.148	0.131	0.781	0.81
	ε_{cc}	9.523	7.892	0.028	0.124	2.029	1.842	2.878	2.82	0.825	0.981	0.425	0.431	0.229	0.26	0.539	0.603
Saafi	$f'cc$	39.99	27.49	0.096	0.091	10.79	10.15	13.12	12.85	0.961	0.96	0.156	0.118	0.154	0.12	0.988	1.017
	ε_{cc}	10.02	8.346	0.012	0.14	2.137	1.941	3.016	2.97	0.818	0.98	0.434	0.462	0.228	0.276	0.525	0.596
Xiao **& Wu**	$f'cc$	173.1	69.98	0.987	4.724	32.77	28.7	45.73	36	0.824	0.766	0.599	0.397	0.668	0.422	1.116	1.062
	ε_{cc}	8.413	6.885	0.002	0.058	1.903	1.724	2.717	2.608	0.829	0.971	0.367	0.324	0.203	0.19	0.551	0.585
Karbahari & Gao	$f'cc$	34.16	24.46	0.047	1.112	10.28	10.55	12.66	12.7	0.962	0.96	0.156	0.119	0.16	0.125	1.02	1.051
	ε_{cc}	3.889	3.343	0.129	0.389	1.313	1.261	1.536	1.511	0.041	-0.047	0.556	0.65	3.53	4.018	6.351	6.179
Lam &Teng	$f'cc$	26.67	29.21	0.504	3.483	11.34	11.93	13.36	13.77	0.961	0.958	0.171	0.136	0.181	0.149	1.054	1.088
	$\varepsilon_{cc(CFRP)}$	4.818	1.933	0.005	0.041	0.817	0.709	1.209	0.966	0.885	0.969	0.326	0.223	0.246	0.167	0.756	0.746
Lam &Teng (Design Model)	$f'cc$	30.36	31.26	0.74	1.76	11.39	11.87	13.5	14.76	0.962	0.959	0.167	0.13	0.181	0.146	1.087	1.12
	$\varepsilon_{cc(CFRP)}$	2.108	0.551	0.002	0.013	0.384	0.209	0.526	0.28	0.883	0.965	0.311	0.211	0.321	0.214	1.032	1.015
BPN Network	$f'cc$	19.23	12.95	0.001	1.142	3.968	5.001	5.558	6.191	0.993	0.991	0.076	0.121	0.078	0.126	1.021	1.036
	ε_{cc}	0.401	0.539	0	0.009	0.095	0.176	0.128	0.246	0.989	0.984	0.105	0.139	0.107	0.158	1.021	1.138

The ANN model seemed to be admissible in simulating the behavior of FRP-confined circular concrete columns, although limited in applicability. Reasonable predictions of the ANN model were derived for values inside the training region. The ability and advantage of using ANNs to model physical operations are presented in this study. Unlike theoretical models, which rely on the assessment of a mathematical equation or solution, the ANN solution process is not formulated clearly. Instead, the relationships are automatically constructed and adapted according to the presented training data. By comparing the outputs of the models to experimental results, it was concluded that the presented ANN model had the best performance in term of predicting the experimental results due to the closest value of R^2 to 1, equal to 0.993 and 0.991 for training and testing of compressive strength and 0.989 and 0.984 for training and testing of strain, respectively. In light of neural techniques to other areas of structural engineering can open new directions for further research.

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