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Technical Paper

Prediction of Compressive Strength of Self-Compacting Concrete using Machine Learning Techniques

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Abstract: The paper deals with the use of Deep Neural Networks (DNN), Artificial Neural Network (ANN), and Random Forest (RF) for estimating the 28- day compressive strength of self-compacting concrete (SCC) containing silica and filler (fly ash, marble powder, and lime powder) with a comparative performance analysis of all techniques. A total of 179 data were taken from literature already published with eight input variables for modelling. The evaluation and comparison of the performance of predicted models were made using the same datasets in training and testing based on correlation coefficient (CC), Coefficient of determination (R2), root mean square error (RMSE), and mean absolute error (MAE). The results showed that proposed model's performance could be improved when training takes place in a Deep Neural Network model with multiple hidden layers. Sensitivity analysis was used to quantify the effect of different variables on concrete strength with coarse aggregate greatly affecting the compressive strength of SCC, followed by fine aggregate content and quantity of silica. A dependable prediction tool is provided through this investigation which suggests that the present model can help scientists and engineers in the optimization of the mixture design of SCC.

Keywords: Compressive strength, Deep neural network, Artificial neural network, Random forest.

1. Introduction

Nowadays, Self- compacting concrete (SCC) is one of the most significant advancements in concrete technology. This concrete can fill and flow the formwork's constrained areas without causing vibration. SCC is a flowable substance placed in formwork and compacted entirely by its weight without vibration or additional processing.

Beginning in 1983, concrete construction durability was the main topic of discussion in Japan for several years. Compaction by skilled workers is essential to creating long-lasting concrete buildings. However, in Japan's construction sector, the quality of construction work has decreased in tandem with the steady decline in the number of skilled personnel. SCC, which can be compressed into every corner of a formwork merely by its weight and without vibrating compaction, was one approach for achieving enduring concrete structures irrespective of construction work. Okamura recognized the requirement for this grade of concrete in 1986 [1]. SCC was first used by Japan in building tunnel bridge construction in the early 1990s, and several SCC bridges have been constructed in Europe. SCC has much potential in highway bridge construction for structural purposes (Fig.1).

Various researchers have conducted several experiments for enhancing the strength of SCC by altering the water-cement ratio, size of aggregates, adding pozzolanic material, etc., to increase the workability of concrete mix. Using chemical admixtures increases the flow ability of the mix. The SCC with supplementary materials can also be developed, which can help use waste or by-products from various industries [2,3]. Some of the researchers have worked on SCC having adequate flow ability, filling ability, and strength by utilizing waste materials like fly ash [4,5], silica fume [6–8], limestone powder [9], and marble powder [10] as SCM's for partial substitution in SCC.

In recent times, machine learning and artificial intelligence (AI) have been widely used in various engineering fields. Techniques involving nonparametric models like a neural network [11–

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13], Floppy logic [14–17] support vector machine models [18], and decision-tree-based algorithms [19] can be used for the prediction of SCC properties. The literature reveals when the training of these models is done with the available data set, they acquire the capability for estimating strength with sufficient accuracy; however, the ability to measure the impact of influencing parameters over strength is still lacking, and also their ability to forecast things is limited by the data requirements. Due to their non-linear approach in modeling, it can set an efficient relationship between large and complex data set of input and output. This further helps in decision-making to generate SCC of desired property as per the need of construction.

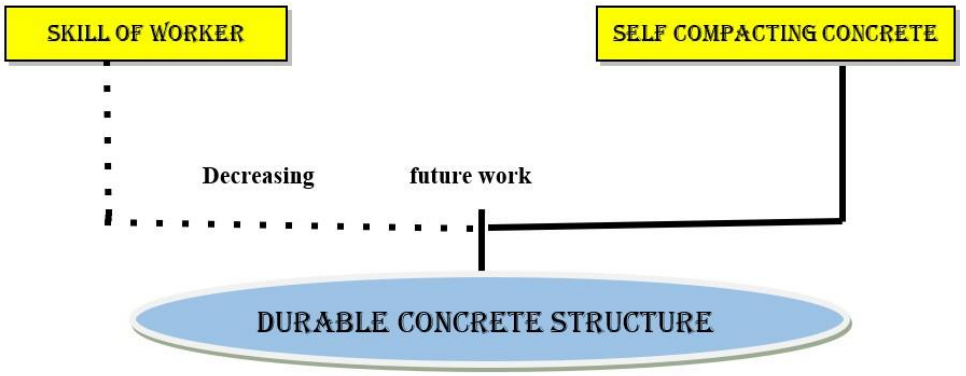

Fig. 1 – Flow chart: Necessity of SCC

During the last few years, Deep Neural Network, Artificial Neural Network (ANN), and Random Forest (RF) have been used widely in various civil engineering problems, as reported by several studies, and has also been observed to outperform the current modeling techniques [20–27]. Deep Neural Network is capable of signifying significantly changing and intricate high-dimensional functions in correlation to conventional neural networks [28]. Two Hybrid AI techniques namely neuro-swarm and neuro-imperialism are proposed to predict the concrete compressive strength. In these two hybrid models, the particle swarm optimization and imperialist competitive algorithm were used to optimize the weights and biases of the ANN to get a higher performance prediction results [29], ensemble for bond strength and fly ash concrete [30,31], similarly soft computing techniques were used for prediction of beam shear strength [32,33].

However, the application of Deep Neural Network, ANN, and RF to prediction of foamed concrete strength [24] have been suggested in a detailed literature review but so far, no application to the prediction of the strength of SCC. Although the algorithms of ANN and DNN are the same, DNN is part of ANN and is used to model high-level abstraction in data. ANN has improved DNN by using advances such as rectified linear units (ReLU)for activation functions.

2. Research Significance

ANN model's success in predicting the compressive strengths of SCC mixes and in simulating physical processes shows that such a numerical technique can be used dependably to produce adequate compressive strengths of SCC mixes within the range of input parameters used to train the model, as opposed to relying on expensive experimental investigation. The resulting information can then be utilized to suggest and formulate mathematical equations that will assist working structural engineers in more precisely predicting the compressive strengths of SCC mixes. The behavior of complex database parameters and their experimental outcomes can be effectively described by machine learning algorithms. Additionally, although ANN has been extensively used to solve real-world financial and electrical engineering problems, its application to real-world structural engineering issues is still restricted to research-related issues. Additionally, the preliminary findings in this work show the key variables that influence the value of compressive strength in SCC mixes.

In recent years, it has been observed that DNN has widespread and much research in various civil engineering problems, as reported by several studies. It has also been observed to outperform the current modelling techniques. DNN is capable of signifying extremely changing and intricate high-dimensional functions in correlation to conventional neural networks. This paper sets a sight on the use of Deep Neural Network, ANN, and RF for calculating SCC's compressive strength and also the current approach helps to understand

the tangled relationship of components of self-compacting concrete with the compressive strength using Deep Neural Network, ANN, and RF. To the author's knowledge, the current DNN concepts, such as rectified linear unit (ReLU) for activation function, dropout, and mini-batch, have not yet been applied to the prediction of concrete strength in the open literature.

3. Methods

3.1 Deep Neural Network (DNN)

A node for processing forms the essential element of a BPNN. The behavior of processing nodes is similar to the biological neuron in performing two functions, i.e., summing input values and then passing this sum through an activation function f for generating output. An activation function, *f*, can be any differentiable function. The layers of BPNN are arranged using all the processing nodes, and the interconnection of each layer is maintained with the following layer. Nodes of the identical layer do not show any interconnection. The input layer in BPNN generally distributes the input data and thus is often used as a distribution structure in which no processing occurs. This layer is followed by one or more processing levels, often called hidden layers; nonetheless, the output layer is the stage after processing. This type of neural network, which has two or more latent layers containing numerous nodes and utilizes advanced numerical demonstration, is known as Deep Neural Network.

Associated weight exists in all interconnections between each node. Net input (n_y) to the unit is calculated by summation of the product of the values passing from input layer through these linkages and associated weight, represented as follows:

$$n_y = \sum_x w_{yx} o_x \qquad (1)$$

Where unit *x* denotes the input unit and w_{yx} denotes the weight of the linkage to unit *y* from unit *x* and $O_x$denotes the output of the unit *x*. This is followed by the activation function for transforming the net input attained by the aforementioned equation to yield an output (O_y) for the unit *y*.

Conventionally, two widely used non-linear activation functions, namely sigmoid and hyperbolic tangent, are used with BPNN. For detailed learning of the intricacies of data, non-linearity is introduced in the neural network using activation functions. It was observed that two major problems with changes around the mid-point of sigmoid and hyperbolic tangent functions are Saturation and sensitivity [34].

The activation function namely rectified linear activation function (ReLU) [31], can be considered a piecewise linear function and a significant algorithmic change in the design of Deep Neural Network [34,35] in the last decade.

In deep learning, ReLU is the ubiquitously used activation function that yields the actual input value as output, provided it is positive or the result is zero. The best feature of this activation function is the simplicity of its training and its superiority to alternative activation mechanisms with Deep Neural Network. The ReLU function is calculated as follows:

$$f(n_j) = max(0, n_j) \qquad (2)$$

Initializing BPNN using correct weights within a reasonable range is crucial for the neural networks to function correctly. It can be obtained by random weight initialization, but it performs poorly. So, a technique for weights initialization for Deep Neural Network was proposed, which was known as Xavier weight initialization [36].

Another important user-defined parameter is the learning rate. Mostly, it is set randomly between 0 and 1. Deep Neural Network employed adaptive gradient descent with an adjustable learning rate technique [34]. Adaptive moment prediction [37] based on an optimal algorithm was used to update network weights during training. Adam involves establishing various user-defined parameters to calculate different learning rates for multiple parameters; hence default values for all user-defined parameters as listed were utilized [37]; it was found to work well with data in this study. Overfitting may be observed in Deep Neural Network due to the overfitting problem because of restricted training data, thus giving a poor performance with test data. Regularization methods are used to prevent the overfitting problem, thereby improving the performance of Deep Neural Network models [34].

The learning algorithm is slightly modified through regularization techniques, enabling better model generalization. Srivastava et al. [38] proposed the introduction of the dropout layer in the Deep Neural Network's design to enhance the model's generalization capability and avoid the overfitting problem.

Dropout is a regularization method used to refine the performance of Deep Neural Network models. By randomly changing these nodes' weights to zero, this approach removes a node

randomly from either a latent or a manifest layer with all its incoming and outgoing connections [38]. Probability *p* (an indication of the likelihood of maintaining the node throughout training, ranging between 0 and 1) is assigned to individual nodes. Besides selecting the activation function, the user-defined hidden layers (i.e., p) dropout layer's likelihood of retention may be optimized using a hit-and-miss method.

Several user-defined features, such as the nodes in every hidden layer, the optimization algorithm, the number and type of hidden layers, the weight initialization method, the batch size (the number of training samples used in one iteration), the number of epochs (one epoch is defined as passing an entire training dataset through the neural network both in the forward and backward direction at least once), and the activation function for output, hidden and surface layers are all included. In this study, WEKA 3.9.5 was utilized to implement Deep Neural Network.

3.2 Artificial neural network (ANN)

Artificial Neural Network is a robust computer tool for modelling complicated non-linear relationships based on biological neural networks. The fundamental building blocks are units (or "nodes") akin to neurons, weighted connections that may be linked to synapses in biological systems. Nodes are the components used in information processing. There may be variations in the number of nodes and their connections. The total number of nodes in the input and output layers corresponds to the number of input and output variables in the data set [39–43]. The appropriate number of nodes in the hidden layer must be discovered by trial and error. More neurons are known to increase learning ability but decrease the ANN's reasoning ability. As a general rule, an ANN should have the smallest number of neurons designed to simulate the training data. Each node-to-node link has a weight that represents a past learning process. The input-output relationship may be approximated by altering these weights. The network must be trained to repeat this input-output relationship to determine the optimal weight. Briefly, the activation rate is specified and sent from the input layer to the output layer through the hidden layers for a given input and the linkages.

The five main aspects of neural network-based modelling are:

1. Data collection, analysis, and depiction of the problem.
2. Architecture selection.
3. Identifying the learning process.
4. Networks' training.
5. The trained network is tested and validated for generalization evaluation.

Following these steps, ANN can produce answers, even errors, and can analyze data very quickly, allowing it to be utilized to solve complicated engineering issues. It can adapt to new data and solve problems with incomplete or inaccurate data. The ANN is made up of a large number of basic processing units known as neurons (Fig. 2). In comparison to statistical approaches, the Artificial Neural Network methodology has the benefit of being able to employ an unlimited number of distinctive characteristics of the phenomena [44]. A good structure, activation function, and a sufficient number of hidden layers are all design considerations in the Artificial Neural Network model.

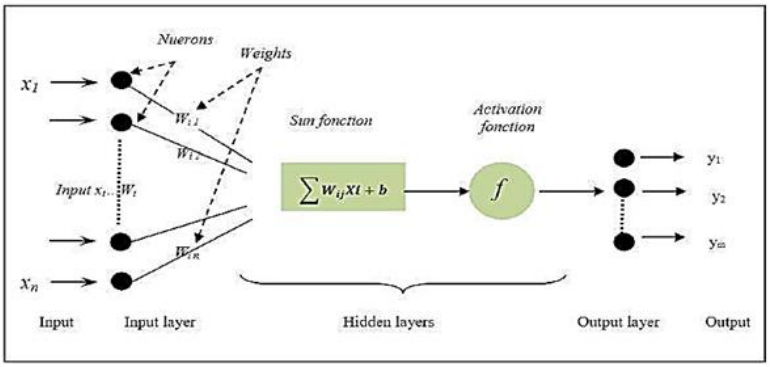

Fig. 2 – Working model of ANN

The five essential parts of an artificial neuron are inputs, weights, sum functions, activation functions, and outputs. Information entering the neural network cell through other external cells is called input. The influence of an input set or another processing element in the introductory level on this process element is expressed by weights. The sum function determines the total effect of inputs and weights on this process element. The net input to a cell is calculated with this function. The

activation function is a function that transforms net input derived from the sum function to produce the cell output [43].

Activation functions come in a variety of shapes and sizes. Non-linear activation functions, such as sigmoid and step functions, are commonly utilized. Because Artificial Neural Networks are learned via experience, they may generalize from previous results to create a new development when an unknown input is introduced to the network. Equation (3) gives the output of a neuron:

$$= \sum_{n=1}^{N} \quad W_n X_n + b \qquad (3)$$

Where X_n= (X_1, X_2, X_3…) represents the N inputs applied to the neuron. W_n represents the weight of the output X_n, and b is the bias.

The back-propagation multilayer perceptron is the most popular and well-known multilayer perceptron training algorithm. The gradient descent method forms its foundation of it. Changing the weight for a brief period reduces the error for a specific training set. Numerous civil engineering applications employ this method. The weight of each neuron shows how much input will influence an output. In the output and input layer, there are precisely as many nodes as variables for output and input.

Fig. 3 shows the input parameters are processed with the help of a single hidden layer, and Fig. 4 shows the same input parameters processed using a double hidden layer. Input parameters are cement, w/b, silica, SP (%), coarse aggregate, fine aggregate, and filler.

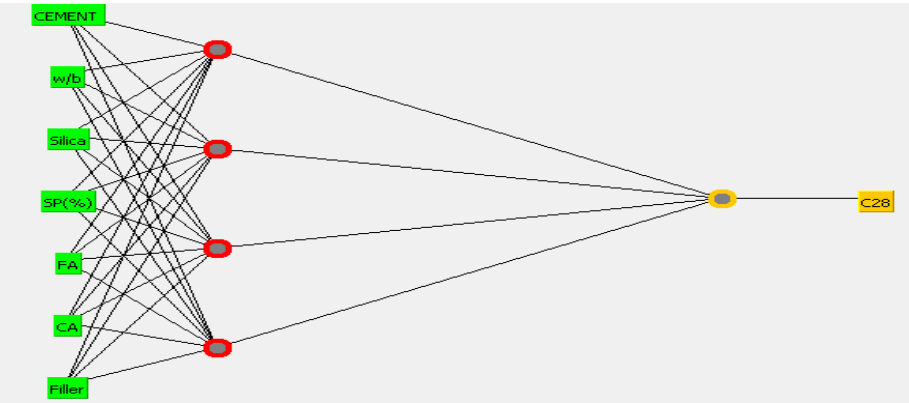

Fig. 3 – ANN with one hidden layer

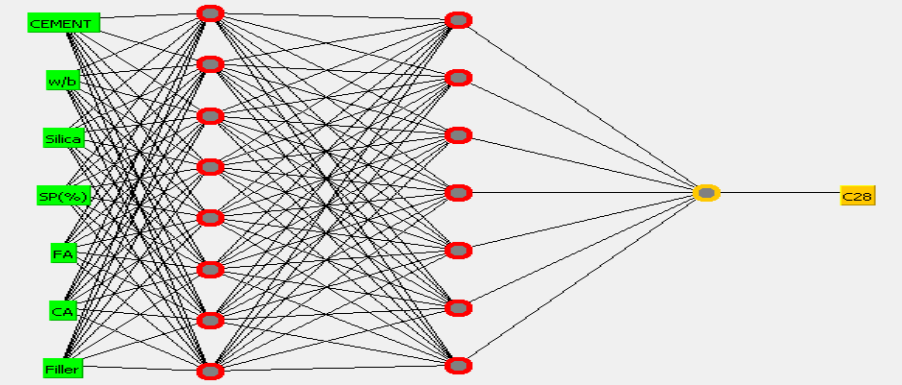

Fig. 4 – ANN with two hidden layer

3.3 Random forest (RF)

Random forest regression was proposed by Breiman in 2001 and is considered an improved classification regression method. Ensemble learning is based on combining multiple classifiers to improve model performance and solve a complex problem. RFs contain the number of decision trees on various subsets of a given data set and take the average value of these datasets to improve the predictive accuracy [45–47]. The more number of trees leads to avoiding overfitting and higher accuracy (Fig. 5). Advantage of RF are as follows:

(a) Training time taken is less than other methods.
(b) Testing time taken is lesser than other methods.
(c) It can retain accuracy even when a significant amount of data is missing.

A prediction is made for each tree formed in the initial phase of the RF's operation before another RF is created by mixing N decision trees. Fig. 5 shows a schematic of the prediction of the Random Forest model.

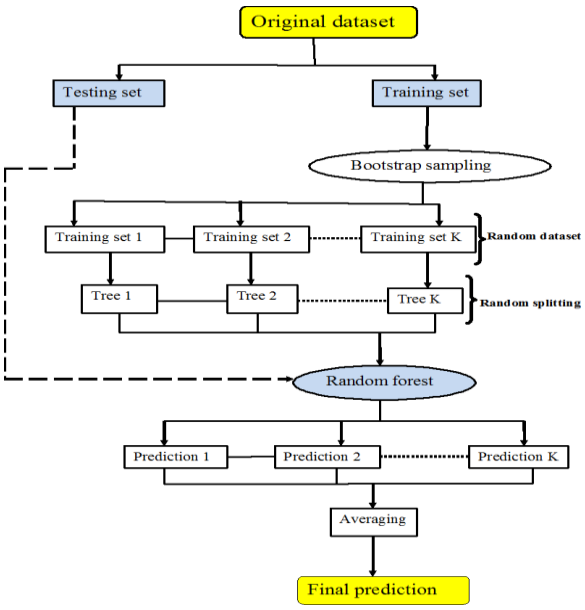

Fig. 5 – Schematic of random forest prediction

4. Results

4.1 Data Base

For the purpose of modeling, large and compressive data were collected from published literature. The sources and number of data taken are mentioned in Table 1, considering characteristics of training and test data used in modelling given in Tables 2 and 3. Data was collected for the quantities of Cement (kg/m^3), W/B, Fine aggregates (kg/m^3), coarse aggregate (kg/m^3), Silica (kg/m^3), Superplasticizer (%) and Filler (kg/m^3). All 179 observations in the research paper comprised the dataset, divided arbitrarily among training models (83%) and test models (17%). The compressive strength of SCC for 28 days was considered an output of this study's models.

Table 1 – Sources of Data

Reference	Authors and publication	Number of Data collected
[48]	Wongkeo et al. / Materials and Design (2014)	20
[49]	Mini and Mohan, Construction and Building Materials (2018)	6
[50]	Atahan and Durgun, Construction and Building Materials (2018)	28
[51]	Bernal et al./Construction and Building Materials (2018)	8
[52]	Choudhary et al./Construction and Building Materials (2020)	12
[53]	M.A. Yaman et al./ Alexandria engineering journal (2017)	42
[57]	Mostafa Jalal et al./Construction and building materials (2015)	8
[54]	S.H.V. Mahalakshmi and V. C. Khed/Materials Today: Proceedings (2020)	4
[55]	B.Behforooz et al./9th International Congress on Civil Engineering, Isfahan University of Technology (2012)	3
[56]	O.M. Ofuyatan et al./International Conference on Engineering for Sustainable World, IOP Publishing (2019)	4
[57]	F.A. Mustapha et al./Materials today: Preceding (2020)	4
[58]	Yuksel Esen and Eyyup Orhan/ KSCE Journal of Civil Engineering (2016)	6
[59]	K.S. Johnsirani, Dr. A. Jagannathan/ International Journal of Engineering Research and Development (2015)	5
[60]	Rita M. Rathod, M.R.Vyawahare/International Journal of Innovative Science, Engineering & Technology (2015)	11
[61]	Hakim Abdelgader et al./Tripoli University, Tripoli, Libya (2014)	12
[62]	H. Szilagyi corbu/Buletinul INCERCOM (2012)	6
	Total Data	179

Table 2 – Features of training data used in modelling

	Cement (Kg/m^3)	Water content (Kg/m^3)	Silica (Kg/m^3)	SP (%)	FA (Kg/m^3)	CA (Kg/m^3)	Filler (Kg/m^3)	C28
Mean	386.78	185.12	26.52	1.13	915.74	763.83	103.69	59.62
Standard Error	7.95	1.90	2.61	0.07	12.88	11.15	8.93	1.21
Median	400.00	180.84	14.00	0.96	927.00	734.00	80.00	56.01
Mode	400.00	180.00	0.00	0.90	1048.00	927.40	0.00	44.50
Standard Deviation	97.03	23.18	31.82	0.91	157.21	136.11	109.02	14.76
Sample Variance	8474.97	311.16	1014.74	0.82	19253.36	14734.71	11892.73	195.55
Kurtosis	0.24	1.00	1.81	6.54	1.25	-1.28	-0.36	-0.40
Skewness	-0.55	0.26	1.37	1.92	-0.65	0.09	0.83	0.64
Range	453.12	108.85	150.00	6.00	772.45	408.00	420.00	60.70
Minimum	146.88	132.00	0.00	0.00	407.55	578.00	0.00	40.30
Maximum	600.00	240.85	150.00	6.00	1180.00	986.00	420.00	101.00
Sum	57630.76	27583.04	3950.85	167.91	136445.4	113810.3	15449.91	8883.34
Confidence Level (95.0%)	15.58	3.72	5.11	0.15	25.24	21.85	17.50	2.37

Table 3 – Features of testing data used in modelling

	Cement (Kg/m^3)	Water content (Kg/m^3)	Silica (Kg/m^3)	SP (%)	FA (Kg/m^3)	CA (Kg/m^3)	Filler (Kg/m^3)	C28
Mean	384.77	0.37	25.58	1.06	935.44	701.35	99.95	58.41
Standard Error	15.76	0.01	5.06	0.15	26.85	17.46	17.55	1.65
Median	400.00	0.37	23.00	0.80	954.00	682.50	100.00	57.35
Mode	400.00	0.40	0.00	0.80	970.00	722.00	0.00	56.50
Standard Deviation	86.31	0.05	27.72	0.80	147.06	95.62	96.14	9.05
Sample Variance	7449.58	0.00	768.25	0.65	21626.76	9142.40	9243.25	81.81
Kurtosis	1.10	0.56	2.05	4.85	4.88	0.07	1.52	1.33
Skewness	-1.23	0.41	1.54	1.75	-1.63	0.87	1.11	0.76
Range	333.00	0.20	100.00	3.85	752.45	339.00	390.00	42.20
Minimum	180.00	0.30	0.00	0.15	407.55	578.00	0.00	43.10
Maximum	513.00	0.50	100.00	4.00	1160.00	917.00	390.00	85.30
Sum	11543.00	11.09	767.30	31.85	28063.25	21040.55	2998.50	1752.38
Confidence Level (95.0%)	30.89	0.02	9.92	0.29	52.62	34.22	34.40	3.24

4.2 Criteria for evaluating model performance

The performance of various techniques in predicting the compressive strength was estimated utilizing different performance evaluation parameters, including correlation coefficient (CC), Coefficient of determination (R2), Root Mean Square Error (RMSE), and Mean Square Error (MSE) given with their expressions in Table 4.

Table 4 – Performance indicators

Reference	Authors and publication
Correlation coefficient	$CC = \frac{\sum_{i=1}^{N}(A_i - \overline{A})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{N}(A_i - \overline{A})^2}\sqrt{\sum_{i=1}^{N}(P_i - \overline{P})^2}}$
Coefficient of determination	$R^2 = \frac{1}{CC}$
Root mean square error	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - A_i)^2}$
Mean absolute error	$MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert P_i - A_i \rvert$
Scattering Index	$R^2 = \frac{RMSE}{\overline{A}}$
Correlation coefficient	$CC = \frac{\sum_{i=1}^{N}(A_i - \overline{A})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{N}(A_i - \overline{A})^2}\sqrt{\sum_{i=1}^{N}(P_i - \overline{P})^2}}$

Where
A = Actual or observed values
P = Predicted values
A = Mean of actual or observed values
N = Number of observations

The degree of linear dependence between the observed value and the predicted value [63] is quantified using the correlation coefficient, with its value close to zero means no association between observed and estimated observations, although when it approaches one signifies a perfect fit among the observed and estimated comments [64]. But the accuracy of the model cannot be evaluated using CC alone, so additional indicators such as R2, RMSE, and MAE can be used to assess the models' appropriateness (in MPa units). Broadly, the higher value of CC and the lower value of R2, RMSE, and MAE lead to a decrease in errors among the observed and estimated values and thereby specify the correctness of models [53].

4.3 Model Development

Preparation of the Deep Neural Network model includes choosing the parameters like the number of hidden layers, dropout layers, p, Activation function, epochs, batch size, instance iterator, type of weight initiation, and Updater. Preparation of the ANN model includes choosing the parameters like the number of hidden layers, batch size, learning rate, momentum, training time, validation set size, and validation threshold. Preparation of a RF model includes choosing the parameters like batch size, bag size percent, max depth, number execution slots, and number iterations. At the start of the design process, the model is trained and developed considering a couple of chief parameters. On assessing the outcomes of the model, if found not satisfactory, the number of primary parameters are increased, successively. Model accuracy is evaluated by comparing the model's results with the actual data.

In the Deep Neural Network, ANN, and RF, the performance and accuracy of the model are validated by various performance indicators such as coefficient of correlation (CC), coefficient of determination (R^2), RMSE and mean absolute error (MAE), which depicts the correlation between output and input parameters. In a nutshell, input parameters consist of nine units which are being processed to output nodes of compressive strength at 28 days. In modeling, the results contain an actual value, predicted value of compressive strength, and error. It also includes network validation through coefficients CC, R^2, RSME, and MAE obtained.

5. Discussion

The main objective of this investigation was the applicability and comparative performance of Deep Neural Network, ANN, and RF using the same datasets (training and testing) taken for both techniques based on correlation coefficient, Coefficient of determination (R2), root mean square error (RMSE) and mean absolute error (MAE) as given in Table 1. The study's outcomes show that the Deep Neural Network model provides a better correlation coefficient than other techniques. Also, other fitness parameters for Deep Neural Network are also better than other techniques. The actual versus predicted values graphs for Deep Neural Network, ANN, and RF are given in Fig. 6 to Fig. 10.

The Deep Neural Network model was optimized using a user-defined parameters algorithm with three hidden layers (120, 100, 80 nodes), batch size=100, epochs=50, Activation function ReLU, and instance iterator=10. The above values were obtained after optimizing the model based on performance indicators after many trials.

The ANN model was optimized using a user-defined parameters algorithm, which employed two hidden layers [left neuron (8), right neuron (7)], learning rate=0.03, momentum=0.5, and iterations=10000. The above values were obtained after the model was optimized using performance indicators following numerous trials.

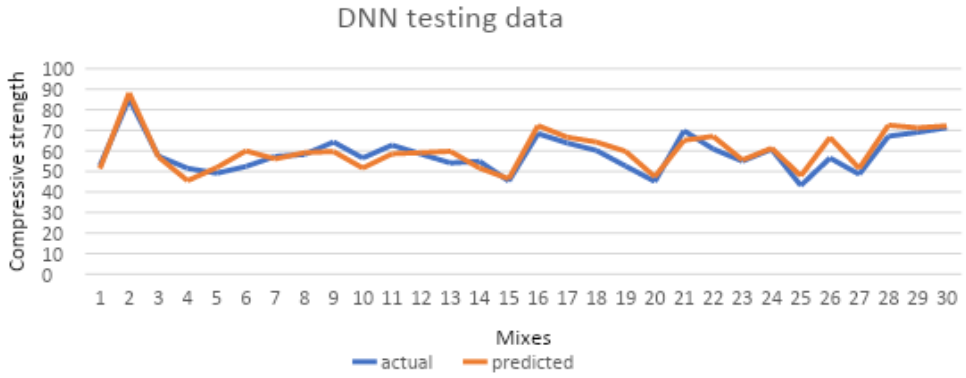

Fig. 6 – Line diagram showing Actual versus Predicted compressive strength by Deep Neural Network for test data

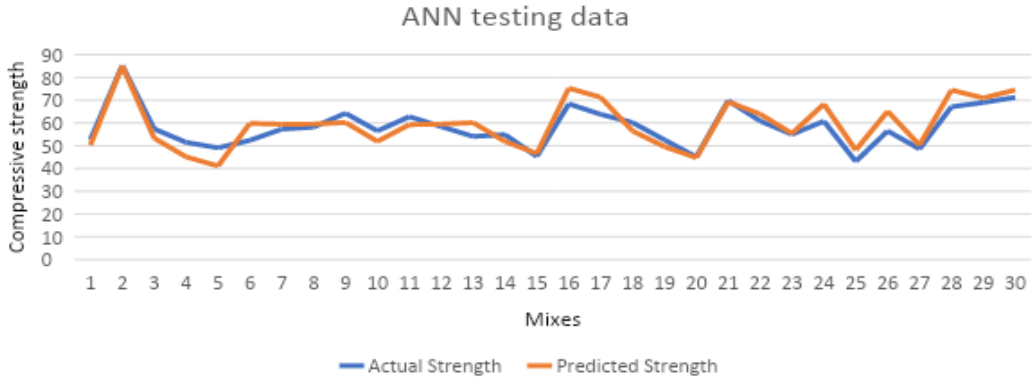

Fig. 7 – Line diagram showing Actual versus Predicted compressive strength by ANN for test data

The RF model was optimized by user-defined parameters using an algorithm that used bag size percent=100, batch size=100, max depth=0, number of execution slots=1, and iterations=100. The values mentioned above were obtained following the model's optimization based on performance indicators following numerous tests.

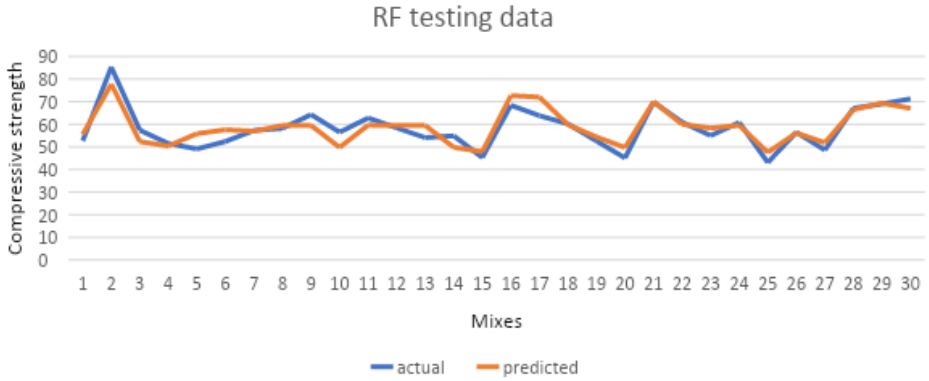

Fig. 8 – Line diagram showing Actual versus Predicted compressive strength by RF for test data

The model's efficiency was compared based on CC, R^2, RSME, and MAE, which are reflected in Table 5. Therefore Deep Neural Network is observed to be a better model to model the prediction of the compressive strength of SCC.

Table - 5 – Performance indicators of DNN, ANN and RF

Fitness parameters	CC	MAE (MPa)	RMSE (MPa)	RAE (%)	RRSE (%)
ANN	0.905	3.873	4.653	54.653	51.848
RF	0.895	3.238	4.001	45.665	44.580
DNN	0.907	3.526	4.259	49.735	47.456

Fig. 9 – Graph for Actual versus Predicted compressive strength by DNN for training data

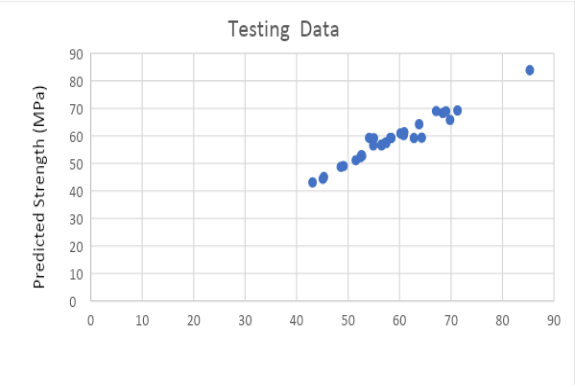

Fig. 10 – Graph for Actual versus Predicted compressive strength by DNN for testing data

6. Sensitivity Analysis

Sensitivity analysis was assessed to discover the vital input parameter in estimating the compressive strength of SCC. The method describes the significance of each limitation in the model to predict compressive strength. Firstly, all the parameters in Table 1, excluding CS, were taken as inputs for the Deep Neural Network model; after that, disregarding single input parameters are summarized in Table 6. Then the model was rebuilt with the same arrangement. After the model structure was adjusted, the sensitivity analysis of the models was started to determine the most valuable parameters. Model performance was altered by eliminating one of the input variables. Considering the absence of every input parameter, the performance of the models was examined using the estimation of indices containing CC, RMSE, and MAE. The outcome of the sensitivity analysis of the Deep Neural Network model is shown in Table 6, which shows the quantity of Coarse aggregate as the most influential parameter in the prediction of compressive strength, followed by fine aggregate and silica, which can be due to the presence of alternative cementitious materials.

Table - 6 – Performance indicators of DNN, ANN and RF

Input Parameters	Removed Parameters	DNN		
		CC	RMSE	MAE
Cement, water, silica, sp, FA, CA, Filler		0.907	4.259	3.526
Water, silica, sp, FA, CA, Filler	Cement	0.815	5.419	4.065
Cement, silica, sp, FA, CA, Filler	Water	0.848	5.305	4.444
Cement, water, sp, FA, CA, Filler	Silica	0.814	6.052	4.841
Cement, water, silica, FA, CA, Filler	SP	0.892	4.215	3.516
Cement, water, silica, sp, CA, Filler	FA	0.801	5.420	3.785
Cement, water, silica, sp, FA, Filler	CA	0.702	6.901	5.689
Cement, water, silica, sp, FA, CA	Filler	0.846	5.076	4.202

7. Limitations and future studies

A computational model for the compressive strengths of SCC mixes is proposed in this paper. If a new value were investigated outside the dataset's bounds, the predicted value would not represent a very accurate estimate of the compressive strengths of SCC mixes due to the dataset's somewhat constrained range. To more precisely predict the compressive strengths of SCC mixes, future study should expand the dataset range. The data gathered for this study can also be used to address other topics, such as how to determine split tensile strength and flexural strength and how those factors relate to compressive strength. The impact of the test data on the development of a new model and the accuracy of the models can be investigated by combining the test data with these data for further study. Additionally, the main objective of this study is to evaluate how well ANN, DNN, and RF learning models perform in estimating the compressive strengths of SCC mixes. Researchers will thus be able to compare the effectiveness of XGBoost and ensemble learning algorithms, with the above techniques, in the future.

8. Conclusions

Self-compacting concrete (SCC) is an eco-friendly material that is a boon for our sustainable development. The merits of SCC can solve many problems like segregation, concrete placement, concrete porosity, congested reinforcement concrete placed, etc. However, compressive strength and workability are significant properties that show its quality. There is a complex association between SCC's ingredients and compressive strength, which can be easily visualized and understood by Artificial Intelligence Techniques. To realize the association between the input and output parameters and the impact of constituents on the compressive strength of SCC models were created using three techniques, i.e., Deep Neural Network, Artificial Neural Network (ANN), and Random forest (RF). The study explores the potential of Deep Neural Network, ANN, and RF models by contrasting their outcomes for estimating the compressive strength of SCC. The primary inference from this study is the outperformance of the Deep Neural Network model over the ANN and RF model on all performance indicators. Therefore, it can be used to accurately estimate the compressive strength of SCC with specified ingredients. The results showed that these techniques have the remarkable capability and possibility for estimating the compressive strength of SCC. Sensitivity results reveal that the coarse aggregate is the utmost significant factor, when the Deep Neural Network model is implemented to estimate compressive strength and is the most pertinent parameter in the approximation of compressive strength for this data set. The highest R^2 value was obtained for DNN technique followed by ANN technique, varying by slight margin. Also, RF technique performed comparative with both DNN and ANN techniques.

In the present scenario, money and time are significant constraints to performing experiments in the laboratory. This artificial intelligence technique can be time-saving, cost, and laborious when conducting investigations to construct SCC. Thus, these approaches can boost and accelerate the rate of technological advancements in civil engineering. Also, a dependable prediction tool is provided, which suggests that the model can help scientists and engineers predict the strength of the Concrete.

Declaration of competing Interest

NIL

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